Team Project 2

Team 4, Role in the Appendix

PART 1 - StreetRx

Summary

The analysis investigates factors that have an impact on the price per milligram of a substance while accounting for potential clustering by location. The data was retrieved from StreetR, and in the case of this analysis the known substance is Oxymorphone, which is an opioid commonly used for severe pain. A multi-level linear regression model is used for exploring factors that impact the price of a substance per milligram. According to the results, it was discovered that source of information, dose strength and bulk purchase are all significantly associated with the price of Oxymorphone. Furthermore, we also observed that there is a heterogeneity in pricing across states.

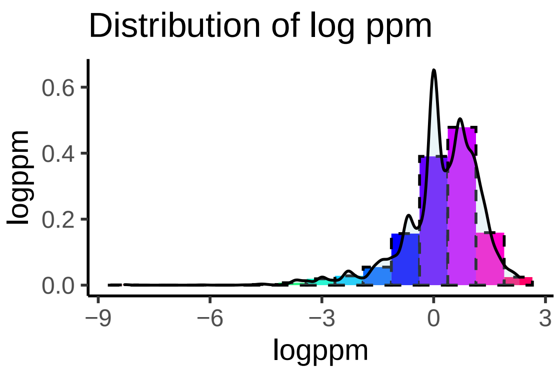
Introduction

StreetRx is a web-based tool that allows users to anonymously submit information regarding various prices paid or heard were paid for prescription grade medications. Prescription opioid diversion and abuse are major public health issues, and street prices provide an indicator of drug availability, demand, and abuse potential. Such data, however, can be difficult to collect and crowdsourcing can provide an effective solution in an era of Internet-based social networks. Data derived from StreetRx generates valuable insights for pharmacoepidemiological research, health-policy analysis, pharmacy-economic modeling, and in assisting epidemiologists and policymakers in understanding the effects of product formulations and pricing structures on the diversion of prescription drugs.For this analysis, we are going to investigate how factors provided in the dataset are associated with pricing of Oxymorphone per milligram as well as heterogeneity in price by location, while accounting for potential clustering by location.

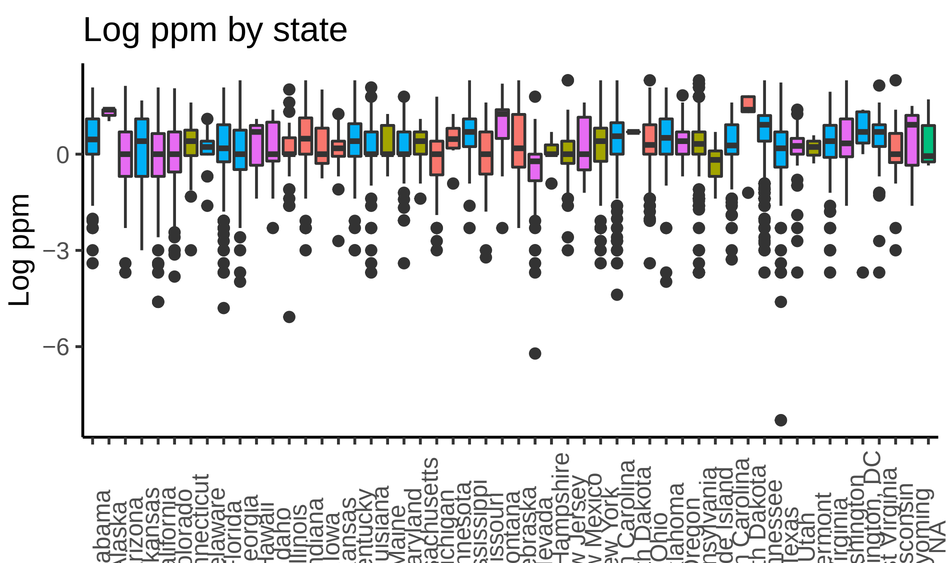
Data

First, we filtered the dataset to our team's assigned drug 'oxymorphone' and left with 4,228 observations. Second, within the 4,228 observations, 11 observations contain missing variables. Since it is small compared to the whole data set, we decided to drop those 11 observations and left with 4,217 observations. Then, we re-organized levels of 'source' into 4 categories including 'Personal', 'Heard it', 'Internet', 'Other' by combining categories with fewer observations. Specifically, we combined 'Internet' and 'Internet Pharmacy' to 'Internet' since both are internet sources. For blank responses or links in the original column, we collapsed them into the 'Other' category. Also, several observations reported 'USA' as 'state', and we changed them to 'Unknown.' Finally, to solve the outlier issue (i.e., people intently report ridiculous prices), we decided to keep data in the left 99% quantile after first inspecting the distribution of price in the dataset and googling the general price range of oxymorphone. Because the distribution of price per mg is highly right skewed and data in the right tail diverges significantly from the normal price range, we decided to cut the right tail, also assuming that people are more likely to report ridiculous high prices than low prices. After removing 1% of data on the right tail, 40 observations were dropped, and we are left with 4,177 observations. After the data cleaning process, we selected columns that we decided to use and stored them into the cleaned dataset, named 'data,' including 'ppm', 'state', 'country', 'USA region', ' source', 'api_temp', 'form temp', 'gmstr' and 'bulk purchase'.

We are interested in different factors related to the price per mg of Oxymorphone while accounting for heterogeneity in different location clusters; therefore, we use ppm (price per mg) as the response variable. We first checked the distribution for the response variable ‘ppm’ using a histogram. The response variable is still right-skewed after removing the outliers, with most variables clustered around 0 and several extreme values at 10. A log transformation of the response ‘ppm’ is applied and denoted as ‘logppm.’ The normality for logppm was checked, and it generally follows a normal distribution with slight left-skewed as the histogram exhibits a bell-shaped curve centered around 0. We decided to use logppm as our final response variable.



To investigate possible relationships with price, we drew box plots for categorical variables (region, source, form, and bulk purchase). According to the ‘logppm by region’ plot, there is no apparent difference between region and logppm other than the south region has a slightly lower logppm; therefore, a random intercept model is considered for ‘region’ in the model selection. By looking at the ‘logppm by state’ graph, we can see that log ppm differs across different states; therefore, a random intercept model for ‘state’ is also considered later in the model selection.



For source, there is no clear difference between log ppm and different sources. For 4,177 observations with our specific drug Oxymorphone, 4,176 observations have the form of pill/tablet, and only 1 observation is suppository as form. Since there is not enough data for suppository form, it is hard to see whether there is a difference in form by EDA, and we decided not to include ‘form’ variable in our model. For bulk purchases, 10+ units at once have around 0 logppm, while purchases with less than 10 units have a higher logppm.

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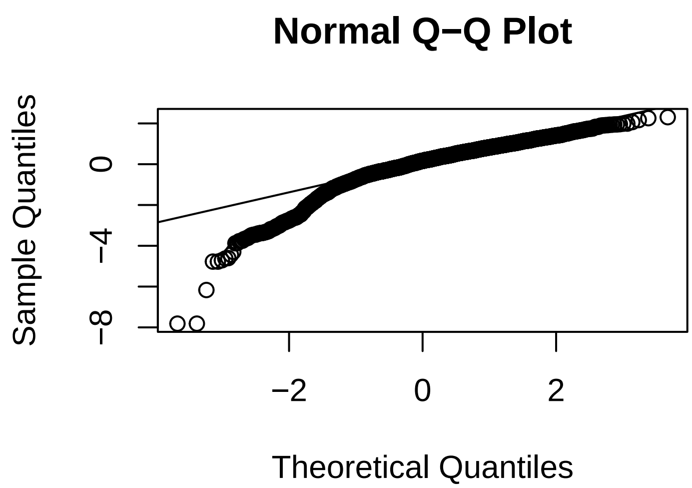
difference in form by EDA, and we decided not to include 'form' variable in our model. For bulk purchases, 10+ units at once have around 0 logppm, while purchases with less than 10 units have a higher logppm. For numeric variables mgstr, there is a weak negative correlation between mgstr and logppm. It means that as the dosage strength in mg of the units purchased increased, log ppm decreased. Additional EDA was presented to test potential interaction effects. We did not see a clear interaction effect between region/source, region/mgstr, bulk purchase/state, source/state, and state/mgstr on log ppm. Therefore, we may not include random slope model for 'state' and 'region'.

Model

To begin with, the baseline model includes all variables of interests (i.e., source, mgstr, bulk purchase) and 'state' as a random intercept. Because `state` is nested within `region` in our dataset, we further ran a model which included every variable in the base model addition with `USA_region` as a random intercept to examine if we need to include `region` as the second level in our model. Based on the result of the anova test for those two models, the p-value is very large (p = 0.43), which indicates that there is no significant difference between the model containing `USA_region` as an additional random intercept and the model which only contains a random intercept of `state`. Therefore, we do not consider including the random intercept of USA_region in the model. Although we did not observe a clear difference in the relationships between predictor variables and log ppm by state/region in EDA, we also tried models which included random slope for the three predictor variables by states. However, the results from anova tests reveal that the random slope terms are all insignificant; therefore we decided not to use random slope. Our final model contains source, mgstr, bulk purchase and state as random intercept, as follows:

$$log(ppm_{ij}) = (\beta_0 + \gamma_{0j}) + \beta_1 Source\_n_{ij} + \beta_2 mgstr_{ij} + \beta_3 Purchase_{ij} + \epsilon_{ij}$$
$$i = 1, ..., n_j;\ j = 1, ..., 51;\ \epsilon_{ij} \sim N(0, \sigma^2);\ \gamma_{0j} \sim N(0, \sum)$$

The model assessment was then performed on the final model to test whether the final model satisfies all four assumptions for linear regression. Within the 'variables vs residual plots,' points are randomly spread throughout the graph, and it means that the regression coefficients have already captured the relationship, so the linearity assumption is satisfied. For the 'residuals vs. fitted' graph, points are spread out randomly. The trend is flat with equal distances within points, which satisfies the independence and equal variance assumptions. Last, although several points on the bottom side do not lie on the 45-degree line, most points lie on the 45-degree line in the Normal QQ plot; therefore, we do not observe clear violations of the normality assumption. We also checked the vif for our final model, the vif are all below two means that there is no multicollinearity issue in our final mode. Outliers for our final model are also checked, and all data points lie below the 0.5 line; therefore, we conclude that there is no outlier issue in our final model.



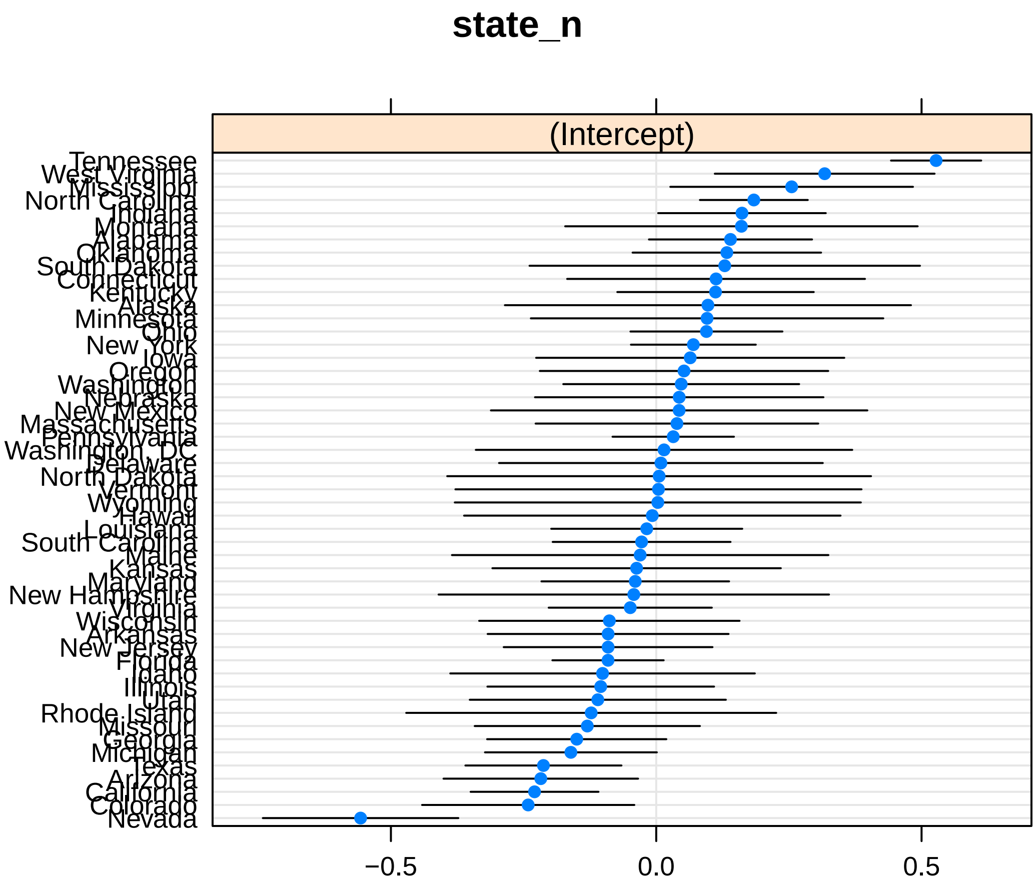
Analysis

According to the model results, every variable in our final model is significant at the 0.05 significance level. If the source is ‘internet’, ‘other’, ‘personal’, the price per mg for oxymorphone is 17.8%, 22.2%, 15.7% lower than the source of ‘heard it’, respectively. We found this result surprising because we did not see any significant difference between different sources. For mgstr (dosage strength in mg), one unit increase of mgstr is associated with an average 2.2% decrease in price per mg while keeping all other variables constant. This result aligns with our EDA that there is a negative correlation between logppm and mgstr. For bulk purchases, if the purchase is 10+ units at once, the price is 15.9% lower in comparison to the price if purchasing less than 10 units. The marginal R-Square and the conditional R-Square is 0.083 and 0.124, respectively.

	logppm		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.79	0.69 – 0.90	**<0.001**
source_n [Internet]	-0.20	-0.35 – -0.04	**0.015**
source_n [Other]	-0.25	-0.33 – -0.17	**<0.001**
source_n [Personal]	-0.17	-0.25 – -0.09	**<0.001**
mgstr	-0.02	-0.02 – -0.02	**<0.001**
bulk_purchase [1 Bulk purchase]	-0.17	-0.25 – -0.09	**<0.001**
Random Effects			
σ^2	0.93		
$\tau_{00\ state\_n}$	0.04		
ICC	0.04		
N_{state_n}	51		
Observations	4159		
Marginal R^2 / Conditional R^2	0.083 / 0.124		

Figure 1: Table 1

We also have a random effect by state. The residual’s estimated standard deviation of 0.96 describes the unexplained variation in the data after taking account of variation across states. The estimated standard deviation of 0.21 describes the across-state variation attributed to the random intercept. For example, in Tennessee, the baseline price of oxymorphone per mg is $3.74, which is higher than the overall average price in the U.S. While in Nevada, the baseline price is $1.26, which is lower than the overall average price in the U.S.



Conclusion

In conclusion, after accounting for clustering by state, source of information, dosage strength and if purchased in bulk (10+ units at once) are found to be statistically significant factors associated with pricing of oxymorphone per milligram. More specifically, the price of oxymorphone per milligram is lower if the source of information is 'Personal', 'Internet' or 'Other' in comparison to the source of 'Heard it'; dosage strength is negatively associated with the price of oxymorphone per milligram. The price is also lower if the drug is purchased in bulk. In addition, we also observed heterogeneity in pricing across states. For instance, the baseline price of oxymorphone in Tennessee is the highest compared to the overall average price in the U.S. On the contrary, Nevada has the lowest pricing compared to the overall average price.

Limitations

1. For the specific drug we picked in the analysis - oxymorphone, does not have variation in the formulation of the drug. Almost all the observations in our dataset have the type of pill as formulation. Therefore, we have to drop this variable in our model as a predictor, but the formulation of the drug can be potentially associated with pricing if we can obtain more data of different formulation types.
2. The dataset we used is crowdsourcing data from streetrx.com, which means the site allows users to anonymously report the price they paid or heard for the drug. As a result, self-reporting may lead to false, or untrustworthy data for our analysis and we did observe unreasonably high prices of oxymorphone in the data.
3. Although the majority of the points fall on the 45-degree line in the QQ-plot, the left tail diverges largely from the 45-degree line. The normality assumption will be better satisfied if we can obtain more credible data for this analysis.

Part 2 - Voting in NC (2020 General Elections)

Summary

This report aims to investigate how different demographic groups voted in the 2020 General Elections in the state of North Carolina. To infer this we have used a multi-level logistic model. The data used contains information about voter registration and voter turn out. This data is aggregated on demographic variables such as *sex*, *county*, *race* etc. For multi-level modeling we have used *county* as the second level as we wanted to understand how different counties vote. We found that the grand mean for Counties varied by 1.15. The predictors *race*, *ethnicity*, *age* and the interactions between *age* and *part_cd* and *sex* and *party_cd* were significant. This confirmed that different counties had different voting patterns. We quantify these differences later in the report.

Introduction

In this report we are primarily interested in understanding how did different demographic groups voted in the 2020 General Elections. Some interesting questions that we aim to answer are – a) Was the voter turn out for females any different from that of male voters after controlling for other factors? Did these turn out rates differ for different party affiliations? b) Did the turn out rates differ by age group for different party affiliations? c) Were the overall odds of voting different for different counties? If so, which counties differ the most from the other counties?

The the report is organized as follows. Data describes the data that we used, how it was merged and an exploratory analysis of this data. Model shows the description of our model fitting and selection. It also includes the interpretation of our model and our main findings. The Conclusion generalizes our investigation and potential limitations of our research.

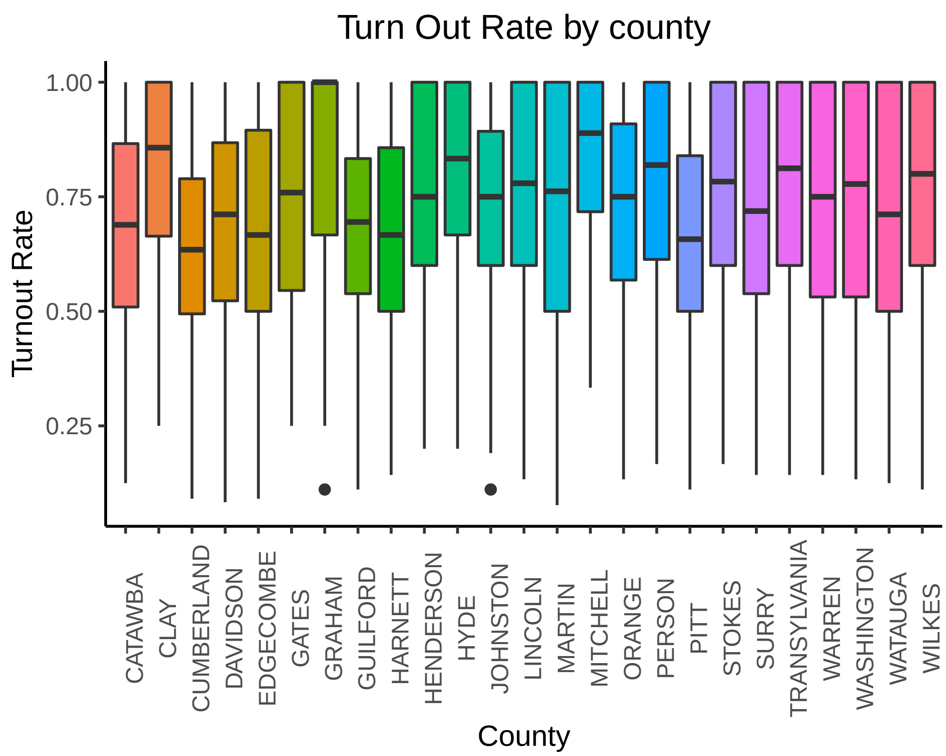
Data

We are working with two datasets, the first dataset (voter_stats_20201103) has information about the aggregate counts of registered voters by demographic variables. The second dataset (history_stats_20201103) has information about the count of voters who actually voted aggregated by demographic variables. We had to aggregate voter_stats_20201103 as it was split by the voting method (in person, by mail). After aggregating the data we merged it with our base dataset (history_stats_20201103). Our merged data had 45,857 rows before sampling. We then randomly sampled for 25 counties. Our final dataset has 11,273 datapoints after removing any rows which had NA's either for the total no. of people who voted or for the registered no. of voters. The counties we worked with are [ORANGE, HARNETT, SURRY, JOHNSTON, TRANSYLVANIA, DAVIDSON, MITCHELL, CATAWBA, CLAY, HENDERSON, GRAHAM, EDGECOMBE, GUILFORD, WATAUGA, CUMBERLAND, MARTIN, LINCOLN, WARREN, GATES, WILKES, HYDE, WASHINGTON, PITT, PERSON, STOKES].

Since our data is aggregated by the demographic variables, our response variable is the number of trials n (number of people who registered to vote) and n - the number of successes (number of people who actually voted) i.e. the voter turn out (1 - 100% voter turn out, 0 - 0% voter turn out) for each county we're working with for different demographic combinations. The predictors include demographic variables *ethnicity, race, age, sex* and *party affiliation* and *county.*

We also noticed that for some datapoints the total no. of registered voters was less than the total no. of people who actually voted. This may be because while some people register at a specific county they end up voting from a different county. But after sampling for our counties there were zero such cases.

Initial EDA of the data revealed that the data is balanced in terms of the data points collected for all counties we sampled for and that the voter turn outs for each county by quite a good percentage. Hence we decided to include a varying intercept for county in our model. The median turn out rate for some counties was very high, *Graham County* for example had a median turn out rate of 100% (as shown below) i.e. majority of the demographic group combinations in this county had a 100% voter turn out rate, which we found quite interesting. We also noticed that the median turn out rate for parties CST and GRE was also 100% because there isn't enough data for these two parties and majority of the people affiliated with this party for whome data was available must have voted. Apart from these parties, the voter turn out for other parties was considerably different prompting us to include a varying slope for *party_cd* in our model. The anova test for the interaction between *party_cd* and *county* was also significant giving us all the more reason to include a varying slope for this predictor.



Some other interesting insights from our EDA were that older people had a higher voter turn out. People who identified and Indian and Black had lower turn out rates compared to other races. Pacific Islanders on the other hand only had 79 data points so making statistical conclusions for this race might be tough. We also observed that Non-hispanic ethnicities had a higher turn out rate. Turn out rates for males and females on the other hand was not very different (even by county) with it being just a little lower for male voters. But the anova test for the interaction between *sex* and *county* was significant.

Additionally, since we're also interested in understanding the effect of *sex* on voter turnout for different party affiliations and effect of *age* on voter turnout for different party affiliations, we made tables to see if we had enough data to explore these interactions. Turns out we're lacking data in some specific bins, for example we don't have enough data for people over 66 affiliated with parties GRE or CST (as these datapoints will get further divided by county). Using hierarchical model here gives us an advantage of borrowing information from other bins which have enough data which wouldn't have been possible with normal logistic regression.

	CST	DEM	GRE	LIB	REP	UNA
Age 18 - 25	63	814	84	248	657	863
Age 26 - 40	108	866	84	295	743	906

	CST	DEM	GRE	LIB	REP	UNA
Age 41 - 65	117	943	73	278	871	934
Age Over 66	34	783	20	107	666	716

Model

For model fitting, we started with a very basic model with all the predictors and a random intercept for county for reasons discussed in the EDA above. This model however failed to converge. To proceed, we removed *sex_code* as a predictor since during the EDA we observed that the voting patterns for female or males voters weren't very different. The **AIC** for this model was **68421**. However, since we're interested in understanding the interaction effects between *sex_code* and *party_cd* and *age* and *party_cd*, for our next model we tried including these interaction effects separately. Both these models failed to converge again. To fix this we tried borrowing information from other groups and included varying intercepts for both these interactions. This way we did not lose information related to the sex of the voters as well. The **AIC** for this model was **64733**, much lower than our base model. This model is shown below.

$$VoterTurnout_i|x_i \sim Bernoulli(\pi_i)$$
$$logit(Pr[VoterTurnout_i = 1]) = \beta_0 + \gamma_{0n[i]}^{county} + \gamma_{0j[i],k[i]}^{age.partyCd} + \gamma_{0l[i],m[i]}^{sex.partyCd} + \beta_1 raceCode_i + \beta_2 ethnicCode_i$$

The problem with this model is that it makes it very hard to interpret the interaction between *sex_code* and *party_cd* and *age* and *party_cd* since we included these as varying intercepts. So for the sake of interpretability, we tried to figure out a way to include these interaction effects as normal interaction terms. For context, one of the reasons for models not converging is that there are too many parametrs that we're trying to estimate. But if that is not one of the reasons we could try fixing the convergence problem by trying new optimizers within the *glmer* function. To do this, we added the *BOBYQA optimizer* in our glmer function. We chose this as our final model as interpreting this model was easier compared to the previous models and it helped us answer all the questions we wanted to. The model equation and is shown below and the summary can be found in the appendix.

$$VoterTurnout_i|x_i \sim Bernoulli(\pi_i)$$
$$logit(Pr[VoterTurnout_i = 1]) = \beta_0 + \gamma_{0m[i]}^{county} + \beta_1 raceCode_i +$$
$$v\beta_2 ethnicCode_i + \beta_3 age_i + \beta_4 sexCode_i + \beta_5 partyCd_i + \beta_6 age_i XpartyCd_i + \beta_7 sexCode_i XpartyCd_i$$

The **AIC** for this model was **64571**. To confirm that this model was better than the base model (but with the BOBYQA optimizer - AIC: 66843) we also performed anova since doing a statistical test, if available, is always better than comparing models based on parameters like AIC. The anova test for this model was significant as also shown below.

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
base_model	21	66843.51	66997.44	-33400.75	66801.51	NA	NA	NA
final_model	46	64571.67	64908.86	-32239.84	64479.67	2321.835	25	0

To assess the model we made the binned residual plot but the plot was not random at all and half the data points were outside the 95% confidence interval. This was because our response variable is not binary (0,1) but aggregated. We could have fixed this by reshaping the data and making the response variable binary but we decided not to spend time on this as this was not the focus of the assignment.

Model Interpretation:

Fixed Effects:

- For any county, in our sample, with female voters in the age group 18 -25 affiliated with the CST party, of Asian race and Hispanic ethnicity, the odds of the voter turn out being 1 or 100% is 1.45.

- For a fixed party affiliation (baseline level), race, sex, and ethnicity, **the odds ratio of a voter in the age bracket 41 - 65 of turning up to vote is 1.9 as compared to a voter falling in the 18 - 25 age bracket.** This aligns with out EDA - older people have a higher voter turn out. These odds are 2.32 for voters in the age bracket of over 66.

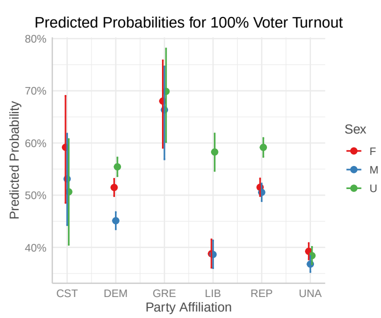
- For a fixed race, sex (baseline level), age bracket (baseline level), and ethnicity, **the odds ratio of a voter affiliated with the Libertarian party of turning up to vote is 0.43** as compared to a voter affiliated with the CST party. These odds ratio are 0.44 for a voter who is not affiliated with any party. This makes sense because if you do not identify with any of the parties then you will have a lower motivation to go and cast a vote.

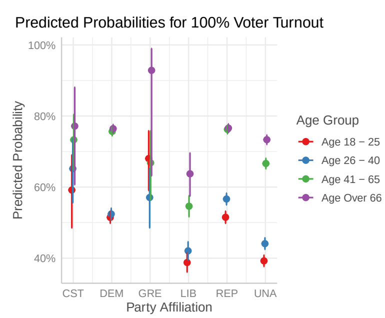
- For a fixed sex, age bracket, party affiliation, and ethnicity, **the odds ratio of a voter of turning up to vote who identifies as black is 0.94 (a 6% decrease) as compared to an Asian voter.** These odds ratio are 1.35 for a voter who identifies as white compared to an Asian voter.

- For a fixed sex, age bracket, party affiliation, and race, **the odds ratio of a voter who identifies as non-Latino of turning up to vote is 1.52** as compared to a voter who identifies as Latino.

Fixed Effects (Interactions):

- For a fixed sex, race, and ethnicity, **the odds ratio of a voter who falls in the age bracket 41-65 and is affiliated with the Democratic party of turning up to vote is exp(0.639251 + (-0.311999) + 0.435856) i.e. 2.144** as compared to voter affiliated with the CST party and in age group 18-25.
- For a fixed age, race, and ethnicity, **the odds ratio of a voter who is male and is affiliated with the Democratic party of turning up to vote is exp((-0.246286) + (-0.311999) + (-0.009305)) i.e. 0.56** as compared to voter affiliated with the CST party and female sex.



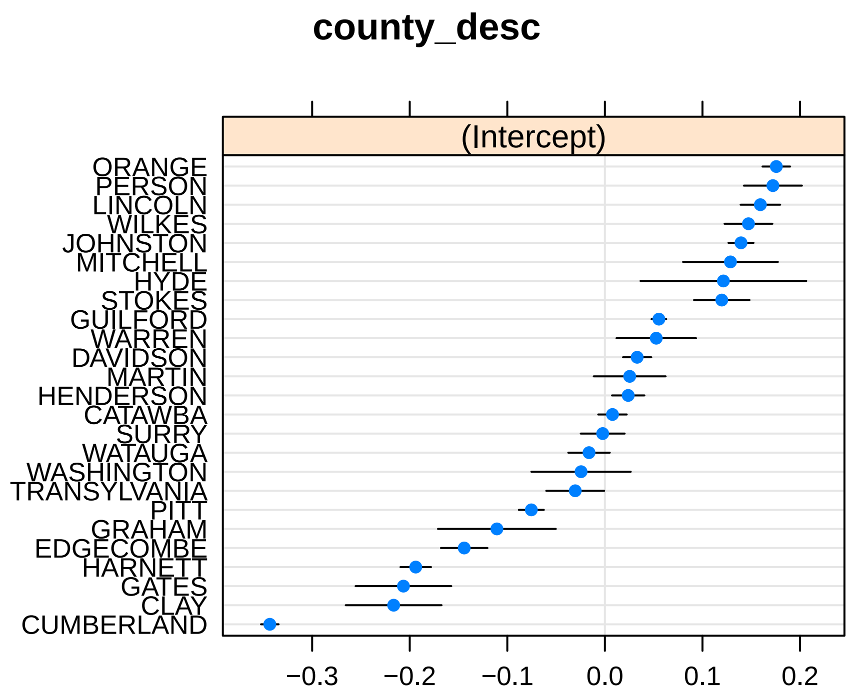


Random Effects:

- The overall variation in the grand mean of the probability of turning up to vote that can be attributed to the county is exp(0.14) i.e. 1.15. This means that if we calculate the standard deviation of the intercepts of all the counties it will be 1.15.

- To understand this better, below is a plot of the variation in the intercepts of different counties in our sample. From the below plot, we can see that the county **Cumberland** has the **lowest odds** for it's voter turn out being 100%. Whereas counties **Orange and Pearson** (and maybe Hyde) have the **highest odds** of their voter turn out being 100%.

```
## $county_desc
```



Conclusion

Countiy **Cumberland** has the lowest odds of having a 100% voter turn-out as compared to the average. County **Orange** had the highest odds of having a 100% voter turn-out. In summary, older people had a higher odds ratio of turning up to vote compared to younger people. Similarly, females had a higher odds ratio of voter turn-out as compared to males. Races Mixed and White had a higher odds ratio of turning up to vote as well as compared to Asians. Following the same pattern, Latinos had a lower odds ratio of voter turn out as compared to non-Latinos. The interaction between age and party affiliation and sex and party affiliation was also found to be significant and the effect has been explained in detail above.

The analysis reported above does suffer from some drawbacks however:

1. We fitted a frequentist model and it may not fully account for the uncertainty in the estimated variance parameters. It also uses an approximation for inference. A better way to model this data would be to use a Bayesian approach.
2. We use *voted_party_cd* variable from *history_stats_20201103* only. Due to this we are unable to account for cases where people change their party affiliations from the time of registration to the time when they actually cast their vote.
3. Some states allow voters to change their county i.e. people can register at one county but actually vote from some other county. For our sample of counties we did not come across such cases but if we were to work with all the counties this might cause a problem in inferring the patterns within different counties.

Designations:

Coordinator: Rashaad Ratliff-Brown

Checker: Ying Feng

Programmer: Dorothy Hou

Writer: Surabhi Trivedi

Presenter: Chenxi Rong

R Code Appendix

Observations	11272
Dependent variable	cbind(total_voters, total_registered_voters - total_voters)
Type	Mixed effects generalized linear model
Family	binomial
Link	logit

AIC	64571.67
BIC	64908.86
Pseudo-R^2 (fixed effects)	0.14
Pseudo-R^2 (total)	0.14

Fixed Effects				
	Est.	S.E.	z val.	p
(Intercept)	0.37	0.22	1.69	0.09
ageAge 26 - 40	0.26	0.20	1.30	0.19
ageAge 41 - 65	0.64	0.21	3.02	0.00
ageAge Over 66	0.85	0.43	1.97	0.05
party_cdDEM	-0.31	0.22	-1.43	0.15
party_cdGRE	0.38	0.29	1.31	0.19
party_cdLIB	-0.83	0.22	-3.72	0.00
party_cdREP	-0.31	0.22	-1.43	0.15
party_cdUNA	-0.81	0.22	-3.72	0.00
race_codeB	-0.06	0.02	-3.79	0.00
race_codeI	-0.01	0.03	-0.44	0.66
race_codeM	0.02	0.02	0.89	0.37
race_codeO	-0.14	0.02	-7.85	0.00
race_codeP	3.61	0.72	4.99	0.00
race_codeU	0.37	0.02	21.33	0.00
race_codeW	0.30	0.01	20.16	0.00
ethnic_codeNL	0.42	0.01	38.81	0.00
ethnic_codeUN	0.33	0.01	30.18	0.00
sex_codeM	-0.25	0.20	-1.23	0.22
sex_codeU	-0.35	0.23	-1.52	0.13
party_cdDEM:sex_codeM	-0.01	0.20	-0.05	0.96
party_cdGRE:sex_codeM	0.17	0.29	0.59	0.56
party_cdLIB:sex_codeM	0.24	0.21	1.17	0.24
party_cdREP:sex_codeM	0.21	0.20	1.03	0.30
party_cdUNA:sex_codeM	0.14	0.20	0.71	0.48
party_cdDEM:sex_codeU	0.50	0.23	2.22	0.03
party_cdGRE:sex_codeU	0.43	0.32	1.36	0.17
party_cdLIB:sex_codeU	1.14	0.24	4.79	0.00
party_cdREP:sex_codeU	0.66	0.23	2.88	0.00
party_cdUNA:sex_codeU	0.31	0.23	1.37	0.17
ageAge 26 - 40:party_cdDEM	-0.22	0.20	-1.11	0.27
ageAge 41 - 65:party_cdDEM	0.44	0.21	2.06	0.04
ageAge Over 66:party_cdDEM	0.27	0.43	0.63	0.53
ageAge 26 - 40:party_cdGRE	-0.73	0.28	-2.55	0.01
ageAge 41 - 65:party_cdGRE	-0.69	0.33	-2.11	0.03
ageAge Over 66:party_cdGRE	0.96	1.12	0.86	0.39
ageAge 26 - 40:party_cdLIB	-0.12	0.20	-0.59	0.56
ageAge 41 - 65:party_cdLIB	0.00	0.22	0.01	0.99
ageAge Over 66:party_cdLIB	0.18	0.45	0.39	0.70
ageAge 26 - 40:party_cdREP	-0.05	0.20	-0.25	0.80
ageAge 41 - 65:party_cdREP	0.47	0.21	2.20	0.03
ageAge Over 66:party_cdREP	0.28	0.43	0.65	0.52
ageAge 26 - 40:party_cdUNA	-0.06	0.20	-0.29	0.77
ageAge 41 - 65:party_cdUNA	0.49	0.21	2.31	0.02
ageAge Over 66:party_cdUNA	0.60	0.43	1.40	0.16

Random Effects		
Group	Parameter	Std. Dev.
county_desc	(Intercept)	0.14

Grouping Variables		
Group	# groups	ICC
county_desc	25	0.01