The Influence of Individual Characterisitcs on Public Transportation Planning*

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Abstract

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```
## Warning: package 'tidyverse' was built under R version 3.5.3

## Warning: package 'ggplot2' was built under R version 3.5.3

## Warning: package 'tibble' was built under R version 3.5.3

## Warning: package 'tidyr' was built under R version 3.5.3

## Warning: package 'readr' was built under R version 3.5.3

## Warning: package 'purrr' was built under R version 3.5.3

## Warning: package 'dplyr' was built under R version 3.5.3

## Warning: package 'stringr' was built under R version 3.5.3

## Warning: package 'forcats' was built under R version 3.5.3

## Warning: package 'lubridate' was built under R version 3.5.3

## Warning: package 'stargazer' was built under R version 3.5.2
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## Warning: package 'corrplot' was built under R version 3.5.3
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## Warning: package 'Hmisc' was built under R version 3.5.3
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## Warning: package 'survival' was built under R version 3.5.3
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## Warning: package 'Formula' was built under R version 3.5.2
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## Warning: package 'dlookr' was built under R version 3.5.3
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## Warning: package 'mice' was built under R version 3.5.3
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1 Literature Review

Allen et al. (2016) study the reasoning of the failure of a referendum on a congestion charging scheme in Edinburgh. Instead of using direct voting data, they conduct a survey after the referendum, which allows them to ask more specific questions. Researchers can gain detailed data by surveying, because the unit of measurement is each individual; however, a possible disadvantage of surveying is that respondents who turn in the questionnaire tend to have stronger attitudes towards the proposal, generating sampling bias. They conclude that people who use cars as the primary transportation mean, demonstrate a misconception of the pricing plan, or question the effectiveness of the scheme at reducing congestion are more likely to oppose it. Their findings can give insights to the similar failure in the Gwinnett referendum. Voters against the proposal could be those who rarely use public transportation and those who are not convinced by the effectiveness of expanding public transit in alleviating the traffic.

Another crucial factor is the accessibility of the proposed transit system. Kinsey et al. (2010) examine the relationship between the distance to the scheduled railway station and voter turnout by studying the Seattle monorail referendum. They introduce the concept of diffused and concentrated benefit/cost. People who live far from the monorail enjoy the diffused benefit of less traffic congestion, and bear the diffused cost of increased tax. People living close to the rail experience the same diffused benefit and cost, but they also gain the concentrated benefit of easily accessing the public good. Finally, those who live very close to the railway have the same benefits and costs, but they also face the concentrated cost such as inconvenience during construction. Since "people are more strongly motivated to avoid losses than to approach gains," they expect a higher turnout rate in farther places with votes for "no," which is verified from their analyses. Besides distance, they also find out precincts with a higher percentage of people of lower socioeconomic status or young people have a lower turnout rate. Interestingly, there is a significant interaction between partisanship and distance, which would be also tested in my study. In essence, the effect of distance on turnout is weakened by partisanship, and vanishes beyond a threshold of distance. Even though my dependent variable is voters' responses rather than turnout, it can be inferred from Kinsey et al.'s findings that people farther away from the transit system would vote against the referendum more. However, the relationship might be non-linear and requires some form of transformation. Regarding the methods, they utilize the spatial lag model to correct for autocorrelation, which is proper to use in my project as well since both studies use precinct-level data.

2 Background

current transportation future plan referendum

3 Data & Methods

3.1 Conceptual model

According to previous research, sociodemographic elements can influence people's voting decisions in the referendum. For example, the effect of income is mixed: on the one hand, people with higher income will pay a smaller portion of their earnings for the implementation of the plan; on the other hand, they will pay a larger amount of tax. Bollino (2008) finds a positive correlation between income and people's willingness to pay for renewable resources. Burkhardt and Chan (2017) separate the influence of income from tax, and discover their opposite effects on voting. Therefore, it is worth considering the relationship between income and percentage of supporters in this referendum. Voters' partisanship attachment is found to be a significant factor as well in Burkhardt and Chan's (2017) paper. Areas with higher proportions of Republicans are less supportive of fiscally costly propositions. In my project, it can be hypothesized that tracts that have a higher proportion of Trump supporters tend to have a lower percentage of agreement to the proposal.

In addition, some factors related to transportation can intuitively shape people's attitudes towards public transit. For example, the areas in which people do not use public transit at all might have a higher percentage of refusal of the proposal. People who have to travel a long time to work are more likely to support the extension plan if it helps save time. These two factors serve as controls in the models.

Finally, people favor the proposition if it benefits them. Specifically, tracts that are not covered by public transport at present but will be covered in the expansion plan are predicted to support the proposal more.

3.2 Data

The ballot results of the Gwinnett County referendum on Mar 19th, 2019 is obtained from a website powered by Scytl, a trusted source of election outcomes. The cross-sectional dataset contains the voting information of all 157 precincts in the county. The dependent variable – the proportion of supporters of the referendum, and the voter turnout rate are calculated from this data source.

The result of the 2016 Presidential Election is chosen to reflect partisanship. A cross-sectional precinct-level election data is obtained from the MIT Election Data and Science Lab website. The number of votes for Trump at each precinct in Gwinnett county comes from this dataset.

Next, cross-sectional sociodemographic characteristics at the census tract level are found in Census Bureau via an R package called `tidycensus`. The data comes from the American Community Survey 5-year estimate published in 2018. The median age and median income are collected here. In addition, the proportion of white, the percentage of people who go to work by public transportation, and the percentage of people who travel more than an hour to work are calculated by dividing the relevant variables by the total population or the survey sample size.

The information on whether the tract enjoys the proximity of public transportation now and future can be acquired from spatial maps and analyses. First, a precinct-level shapefile of Gwinnett County made in 2018 is obtained from the Georgia General Assembly. Gwinnett County maps with current and proposed future public transit systems are available on the Gwinnett County government website. I select the short-range expansion plan (Y2020 – 2025) because the cost and benefit of the expansion in the far future are discounted more. After modifications in QGIS software, the maps are then transformed into spatial data readable in R. Five-hundred-meter buffer zones are created around bus and railway routes. The categorical variable *current_plan* has four levels: 1 represents no transportation near this tract at present and in the future; 2 represents the tracts that are accessible to public transit currently but not in the future; 3 stands for the tracts that do not have transit at present but will do in the expansion plan; 4 represents the tracts that have and will have public transit for now and for the future.

As noted above, both referendum and 2016 election data are collected at the precinct level. However, the other datasets are performed at the census tract level. Therefore, referendum and election data are redistributed by the areas shared by the precinct and the tract. See the data appendix for detailed steps of

Table 1: Variable definitions

Variable name	Description
GEOID	The geographic identifier of the census tract
medage	The median age of the population in the tract
medincome	The median income of the population in the tract
white_pct	The percentage of white population in the tract
public_pct	The percentage of people who go to work by public transportation (excluding taxi or cab)
time_pct	The percentage of people who travel more than an hour to work
trump_pct	The estimated percentage of votes for Donald Trump in that tract
voter_turnout	The estimated percentage of voters who voted in this referendum in the tract
yes_pct	The estimated percentage of voters who voted yes in this referendum in the tract
plan_yes	Whether the tract is covered by the public transportation now and in the short-range, defined by whether any transportation is available within 500 meters. 1 stands for the tract doesn't have transit both now and in the short-range plan. 2 stands for the tract has transit now but not in the short-range plan. 3 stands for the tract that doesn't have transit now and will have in the future. 4 stands for the tract that has public transit both now and in the future

transformation.

The final dataset joins the datasets above by GEOID. It is cross-sectional, measured with the unit of the census tract. A description of the variables can be found in *Table 1*.

Table 2: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
medage	113	35.56	4.58	26	32.8	38.8	52
medincome	113	69,439.24	24,358.44	33,020	51,429	82,845	156,136
white_pct	113	0.48	0.15	0.17	0.38	0.61	0.89
public_pct	113	0.01	0.01	0	0.002	0.02	0
time_pct	113	0.16	0.05	0.04	0.12	0.20	0.31
trump_pct	113	0.40	0.15	0.11	0.27	0.52	0.69
voter_turnout	113	0.16	0.06	0.05	0.13	0.18	0.37
yes_pct	113	0.53	0.14	0.27	0.42	0.61	0.84

```
data_numeric <- final_data %>%
  select(-c(current_plan,GEOID))


data_cor = cor(data_numeric)


data_cor_1 <- rcorr(as.matrix(data_numeric))
M <- data_cor_1$r
p_mat <- data_cor_1$P
```

```r
corrplot(M, type = "upper", order = "hclust",
         p.mat = p_mat, sig.level = 0.05)
```

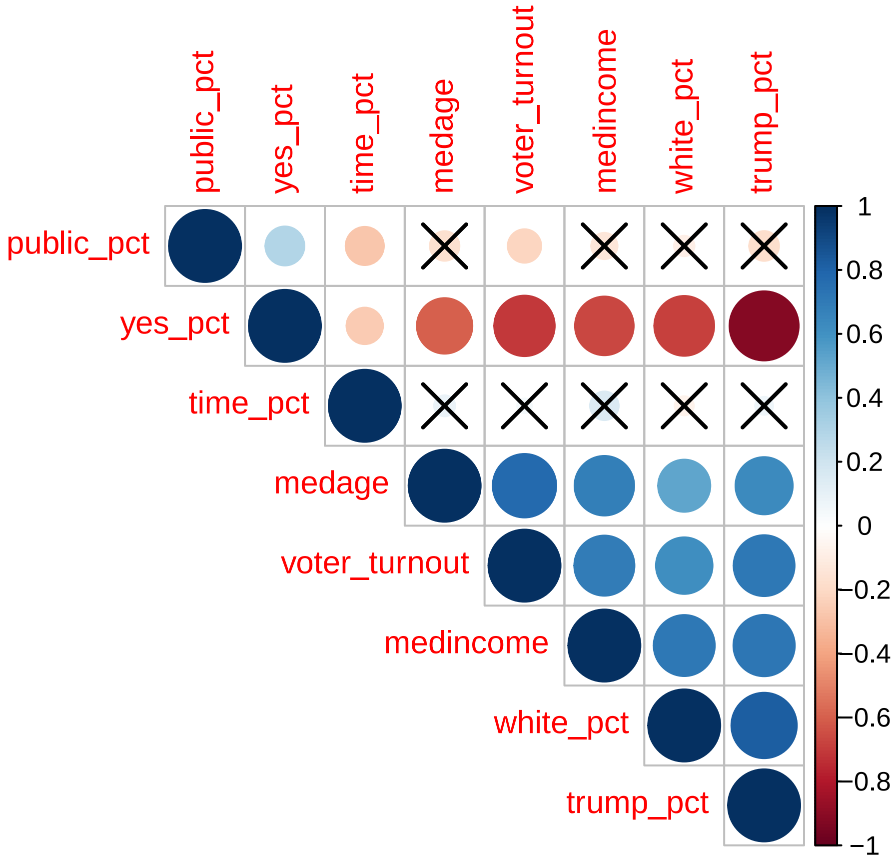


Table 2 lists the summary statistics. Median income is skewed to the right, with a few tracts demonstrating high income levels. Such a pattern of inequality is universally observed.

The usage of public transit is low. On average, only one percent of the population relies on public transportation to go to work. As proved by later analyses, the distribution is highly skewed, and will be transformed in some models. **public_pct max needs to be fixed**

The variable *current_plan* is not in *Table 2* because it is a categorical variable. In sum, 31 tracts do not have access to public transport within 500 meters, both now and in the short-range. There is one tract that is categorized as 2, indicating that it has public transit at present, but not in the short-range proposition. It could be due to the plan of reducing circuitous routing. Twenty-two tracts do not enjoy the proximity of public transport now, but will in the short-range. Lastly, 59 tracts have public transit available both at present and in the short-range plan. Since a level of this variable contains only one value ("2"), problems with degrees of freedom will potentially arise.

A correlation matrix is created from `corrplot` package to investigate the correlation between each pair of factors (see *Figure ???*). Positive correlations are in blue colors, and negative correlations are in red colors. The magnitude is reflected by the color intensity and the size of the dot. Non-significant ($p > 0.05$) correlations are marked with a cross. *Current_plan* is omitted in the matrix because it is categorical. The dependent variable *yes_pct* is significantly correlated with every independent variable. *Medage*, *voter_turnout*, *medincome*, *white_pct*, and *trump_pct* are all strongly positively correlated with each other, and all of them are negatively associated with *yes_pct*. Given the number of strong, significant correlations among the factors, it is essential to check collinearity in the regression model.

The major limitation of the data is the unit conversion from precinct to census tract. Such a method assumes that residents in one precinct have the same characteristics, and population density is identical. Clearly, the assumptions cannot be satisfied in a real dataset.

3.3 Model specification

Four models are tested in the analysis.

Model 1 adopts linear regression model with all the original variables:

$$yes\_pct_t = \beta_0 + \beta_1 medincome_t + \beta_2 white\_pct_t + \beta_3 trump\_pct_t + \beta_4 current\_plan_t + \beta_5 medage_t + \beta_6 public\_pct_t + \beta_7 time\_pct_t + \beta_8 voter\_turnout_t + \epsilon_t$$

where t indexes census tract. Since all variables are measured in the same scope, no fixed effects are tested. The dependent variable is *yes_pct*, the proportion of supporters of the referendum in a tract. Independent variables include *medincome*, *white_pct*, *trump_pct*, and *current_plan*. For more information about these variables, refer to *Table ???*. I hypothesize that the effect of *medincome* is ambiguous. As explained in the Conceptual Model section, people with higher income pay a larger amount of tax, but the tax takes up a smaller portion of their earnings compared to those with lower income. *White_pct* is hypothesized to have a negative effect on *yes_pct*, based on the negative correlation between the two variables. A higher percentage of Trump supporters is expected to predict a lower percentage of votes for "yes" in the referendum, as evidenced by common sense and previous literature (???). Finally, since tracts that do not have public transit now and will have it in the short-range benefit the most from the proposition, I predict that the tracts with this feature will have a higher level of *yes_pct* than the others.

Medage, *public_pct*, *time_pct*, and *voter_turnout* add to the model as controls. For example, tracts with higher voter turnout are hypothesized to have a lower *yes_pct*, according to the rule of loss aversion – people who believe the referendum incur losses to them are inclined to participate in the referendum actively and vote against it, but people who like the proposition are less motivated to vote in nature.

Medincome, *public_pct* and *voter_turnout* are found to be positively skewed. Thus, *Medincome*, *public_pct* and *voter_turnout* are found to be positively skewed. Thus, Model 2 uses multiple linear regression after log or square root transformation on these three variables. Among them, *public_pct* is transformed by adding 0.01 to the original number and taking its natural log. Since many of its values are 0, a constant has to add to the variable before taking log transformation.

$yes\_pct_t = \beta_0 + \beta_1 log(medincome_t) + \beta_2 white\_pct_t + \beta_3 trump\_pct_t + \beta_4 current\_plan_t + \beta_5 medage_t + \beta_6 log(public\_pct_t + 0.01) + \beta_7 time\_pct_t + \beta_8 \sqrt{voter\_turnout_t} + \epsilon_t$

4 Results & Discussion

4.1 model 1: linear

```
mod1 <- lm(data = final_data, yes_pct ~ medage + medincome + white_pct
           + public_pct + time_pct + trump_pct + voter_turnout +
             current_plan)
summary(mod1)
```

Call: lm(formula = yes_pct ~ medage + medincome + white_pct + public_pct + time_pct + trump_pct + voter_turnout + current_plan, data = final_data)

Residuals: Min 1Q Median 3Q Max -0.103714 -0.032077 -0.002399 0.030226 0.101740

Coefficients: Estimate Std. Error t value Pr(>|t|)

(Intercept) 8.041e-01 4.707e-02 17.085 < 2e-16 ***medage 2.738e-03 1.481e-03 1.849 0.06739 .***

medincome 1.326e-07 2.930e-07 0.453 0.65183

white_pct 1.143e-01 5.326e-02 2.147 0.03420

public_pct 8.173e-01 3.382e-01 2.417 0.01743 *

time_pct -3.057e-01 9.048e-02 -3.378 0.00103 trump_pct -8.859e-01 5.709e-02 -15.517 < 2e-16

voter_turnout -3.257e-01 1.262e-01 -2.582 0.01125

current_plan2 1.888e-02 4.399e-02 0.429 0.66866

current__plan3 -3.176e-02 1.201e-02 -2.645 0.00945 current__plan4 1.612e-02 1.155e-02 1.395 0.16606 — Signif. codes: 0 '*' ***0.001*** '' *0.01* '' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04197 on 102 degrees of freedom Multiple R-squared: 0.9174, Adjusted R-squared: 0.9093 F-statistic: 113.2 on 10 and 102 DF, p-value: < 2.2e-16

```
library(margins)
```

```
## Warning: package 'margins' was built under R version 3.5.3
```

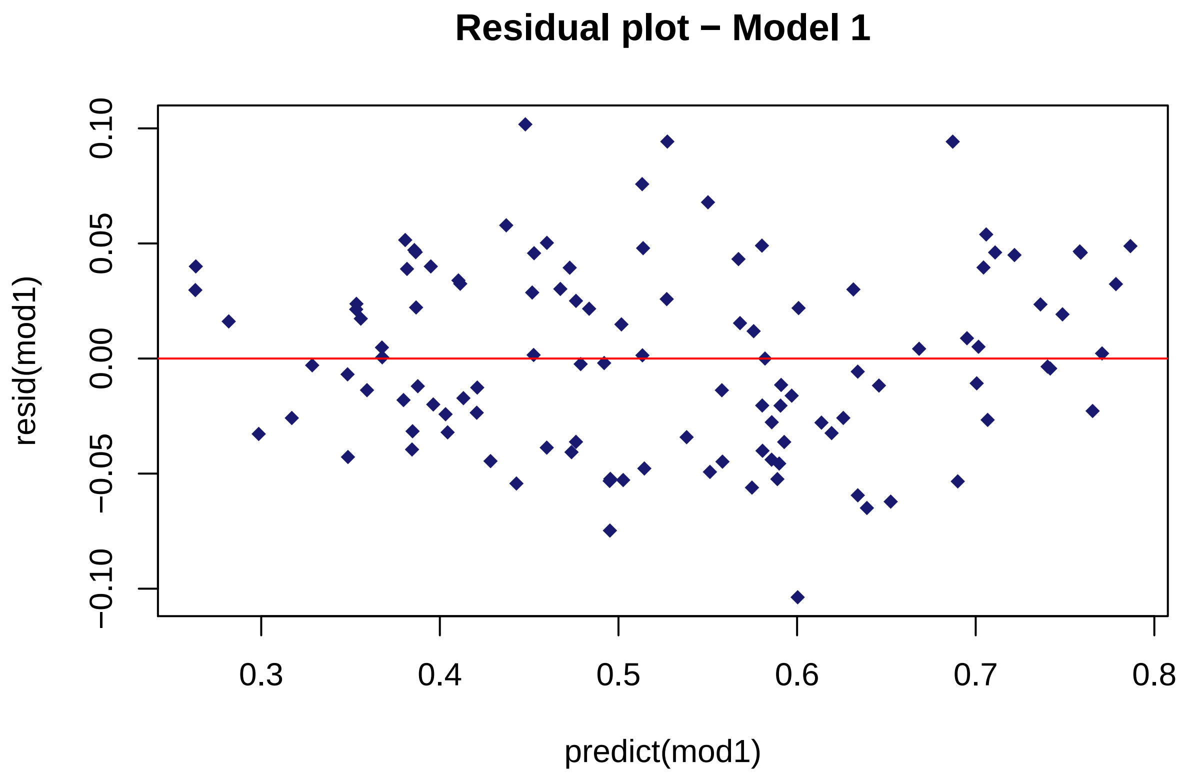
```
summary(margins(mod1))
```

```
    factor     AME     SE        z      p   lower   upper
```

current__plan2 0.0189 0.0440 0.4292 0.6678 -0.0673 0.1051 current__plan3 -0.0318 0.0120 -2.6453 0.0082 -0.0553 -0.0082 current__plan4 0.0161 0.0116 1.3949 0.1630 -0.0065 0.0388 medage 0.0027 0.0015 1.8488 0.0645 -0.0002 0.0056 medincome 0.0000 0.0000 0.4525 0.6509 -0.0000 0.0000 public__pct 0.8173 0.3382 2.4168 0.0157 0.1545 1.4801 time__pct -0.3057 0.0905 -3.3784 0.0007 -0.4830 -0.1283 trump__pct -0.8859 0.0571 -15.5168 0.0000 -0.9978 -0.7740 voter__turnout -0.3257 0.1262 -2.5816 0.0098 -0.5729 -0.0784 white__pct 0.1143 0.0533 2.1466 0.0318 0.0099 0.2187

4.1.1 model 1 assumption checking

```
plot(predict(mod1),resid(mod1),col="midnightblue",pch=18,main="Residual plot - Model 1")
abline(0,0,col="red")
```



4.1.2 collinearity:

```r
library(car)
```

```
## Warning: package 'car' was built under R version 3.5.3
```

```
## Loading required package: carData
```

```
## Warning: package 'carData' was built under R version 3.5.3
```

```
##
## Attaching package: 'car'
```

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

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

```r
vif(mod1)
```

GVIF Df GVIF^(1/(2*Df))

medage 2.921005 1 1.709095 medincome 3.237296 1 1.799249 white_pct 3.900578 1 1.974988 public_pct 1.163004 1 1.078427 time_pct 1.563279 1 1.250312 trump_pct 4.533128 1 2.129114 voter_turnout 3.372750 1 1.836505 current_plan 1.853504 3 1.108321

all below 5: good, no collinearity problem

```r
extreme <- data.frame(medage = c(max(final_data$medage), min(final_data$medage)),
                      medincome = c(max(final_data$medincome), min(final_data$medincome)),
                      white_pct = c(max(final_data$white_pct), min(final_data$white_pct)),
                      public_pct = c(max(final_data$public_pct), min(final_data$public_pct)),
                      time_pct = c(min(final_data$time_pct), max(final_data$time_pct)),
                      trump_pct = c(min(final_data$trump_pct), max(final_data$trump_pct)),
                      voter_turnout = c(min(final_data$voter_turnout), max(final_data$voter_turnout)),
                      current_plan = c(3,2))

extreme <- extreme %>%
  mutate(current_plan = as.factor(current_plan))
```

4.1.3 Predicted values

```r
values_compare <- final_data %>%
  mutate(predicted = predict(mod1, newdata = final_data)) %>%
  select(yes_pct, predicted)
```

```r
predict(mod1, newdata = extreme)
```

```
     1          2
```

0.95747322 0.09349941

4.2 model 2: no interaction, logistic

```r
mod2 <- glm(data = final_data, yes_pct ~ medage + medincome + white_pct + public_pct + time_pct + trump_
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```r
summary(mod2)
```

Call: glm(formula = yes_pct ~ medage + medincome + white_pct + public_pct + time_pct + trump_pct + voter_turnout + current_plan, family = "binomial", data = final_data)

Deviance Residuals: Min 1Q Median 3Q Max

-0.224855 -0.066351 -0.001643 0.067049 0.208799

Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) 1.328e+00 2.320e+00 0.572 0.567 medage 1.070e-02 7.223e-02 0.148 0.882 medincome 6.272e-07 1.435e-05 0.044 0.965 white_pct 5.506e-01 2.639e+00 0.209 0.835 public_pct 3.528e+00 1.715e+01 0.206 0.837 time_pct -1.390e+00 4.468e+00 -0.311 0.756 trump_pct -3.779e+00 2.844e+00 -1.329 0.184 voter_turnout -1.441e+00 6.219e+00 -0.232 0.817 current_plan2 5.722e-02 2.128e+00 0.027 0.979 current_plan3 -1.378e-01 5.889e-01 -0.234 0.815 current_plan4 5.908e-02 5.632e-01 0.105 0.916

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 9.05063  on 112  degrees of freedom
```

Residual deviance: 0.82869 on 102 degrees of freedom AIC: 135.96

Number of Fisher Scoring iterations: 4

model 1 & 2 table

Table 3: Initial regression results

	Dependent variable:	
	yes_pct	
	OLS	*logistic*
	(1)	(2)
medage	0.003*	0.011
	(0.001)	(0.072)
medincome	0.00000	0.00000
	(0.00000)	(0.00001)
white_pct	0.114**	0.551
	(0.053)	(2.639)
public_pct	0.817**	3.528
	(0.338)	(17.153)
time_pct	−0.306***	−1.390
	(0.090)	(4.468)
trump_pct	−0.886***	−3.779
	(0.057)	(2.844)
voter_turnout	−0.326**	−1.441
	(0.126)	(6.219)
current_plan2	0.019	0.057
	(0.044)	(2.128)
current_plan3	−0.032***	−0.138
	(0.012)	(0.589)
current_plan4	0.016	0.059
	(0.012)	(0.563)
Constant	0.804***	1.328
	(0.047)	(2.320)
Observations	113	113
R^2	0.917	
Adjusted R^2	0.909	
Log Likelihood		−56.978
Akaike Inf. Crit.		135.955
Residual Std. Error	0.042 (df = 102)	
F Statistic	113.224*** (df = 10; 102)	
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Initial linear and logistic regression results	

4.3 model 3: no interaction, some transformations, linear

4.3.1 step 1: find the skewed variables

medincome, public_pct, voter_turnout

step 2: transform them

```
data_tf <- final_data %>%
  mutate(log_medincome = log(medincome),
         log_public_pct = log(public_pct + 0.01),
         sqrt_voter_turnout = (voter_turnout)^0.5) %>%
  select(-c(medincome, public_pct, voter_turnout))
find_skewness(data_tf)
```

integer(0)

4.3.2 step 3: model them

```
mod3 <- lm(data = data_tf, yes_pct ~ medage + log_medincome + white_pct + log_public_pct + time_pct + tr
summary(mod3)
```

Call: lm(formula = yes_pct ~ medage + log_medincome + white_pct + log_public_pct + time_pct + trump_pct + sqrt_voter_turnout + current_plan, data = data_tf)

Residuals: Min 1Q Median 3Q Max -0.099920 -0.031591 -0.003479 0.027983 0.098568

Coefficients: Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.031840 0.218778 4.716 7.64e-06 ***medage 0.003603 0.001511 2.384 0.01899***

log_medincome -0.008331 0.022302 -0.374 0.70952

white_pct 0.116703 0.050746 2.300 0.02350 *

log_public_pct 0.022304 0.008263 2.699 0.00814 time_pct -0.281374 0.089698 -3.137 0.00223 **

trump_pct -0.856963 0.058590 -14.626 < 2e-16 * **sqrt_voter_turnout -0.319107 0.103460 -3.084 0.00263** current_plan2 0.021184 0.043430 0.488 0.62677

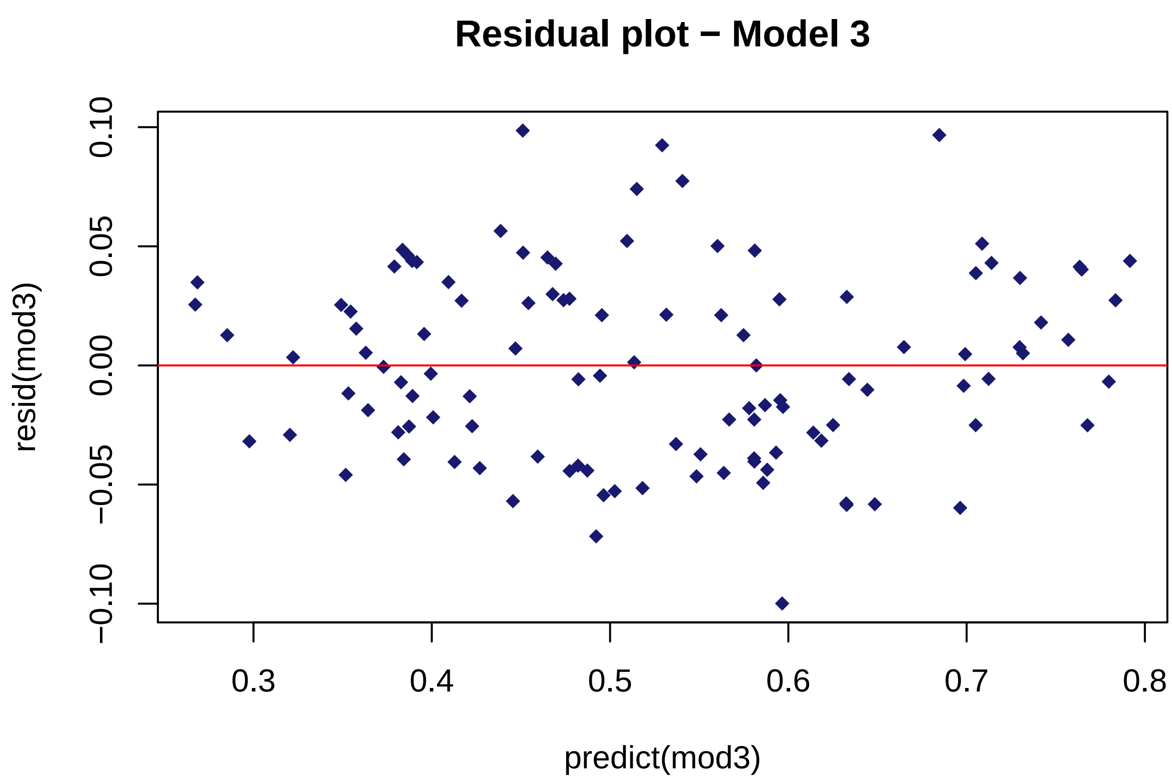
current_plan3 -0.033367 0.011777 -2.833 0.00555 ** current_plan4 0.013583 0.011459 1.185 0.23864

— Signif. codes: 0 '' ***0.001*** '' *0.01* '' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04125 on 102 degrees of freedom Multiple R-squared: 0.9202, Adjusted R-squared: 0.9123 F-statistic: 117.6 on 10 and 102 DF, p-value: < 2.2e-16

4.3.3 model 3 assumption checking

```
plot(predict(mod3),resid(mod3),col="midnightblue",pch=18,main="Residual plot - Model 3")
abline(0,0,col="red")
```



4.3.4 collinearity:

```
vif(mod3)
```

```
                 GVIF Df GVIF^(1/(2*Df))
```

medage 3.149713 1 1.774743 log_medincome 3.738783 1 1.933593 white_pct 3.666112 1 1.914709 log_public_pct 1.149252 1 1.072032 time_pct 1.590210 1 1.261035 trump_pct 4.942057 1 2.223074 sqrt_voter_turnout 3.628296 1 1.904809 current_plan 1.883541 3 1.111295

all below 5: no collinearity

4.4 model 4: transformation, logistic

```
mod4 <- glm(data = data_tf, yes_pct ~ medage + log_medincome + white_pct
           + log_public_pct + time_pct + trump_pct + sqrt_voter_turnout +
              current_plan, family = "binomial")
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```
summary(mod4)
```

Call: glm(formula = yes_pct ~ medage + log_medincome + white_pct + log_public_pct + time_pct + trump_pct + sqrt_voter_turnout + current_plan, family = "binomial", data = data_tf)

Deviance Residuals: Min 1Q Median 3Q Max

-0.21662 -0.06950 0.00000 0.06082 0.20908

Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) 2.30500 10.89739 0.212 0.832 medage 0.01489 0.07514 0.198 0.843 log_medincome -0.03485 1.11172 -0.031 0.975 white_pct 0.56326 2.55987 0.220 0.826 log_public_pct 0.09511 0.41908 0.227 0.820 time_pct -1.28743 4.50172 -0.286 0.775 trump_pct -3.64687 2.95956 -1.232 0.218 sqrt_voter_turnout -1.45781 5.21572 -0.280 0.780 current_plan2 0.06583 2.13728 0.031 0.975 current_plan3 -0.14496 0.58781 -0.247 0.805 current_plan4 0.04787 0.56805 0.084 0.933

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 9.0506  on 112  degrees of freedom
```

Residual deviance: 0.7965 on 102 degrees of freedom AIC: 136.15

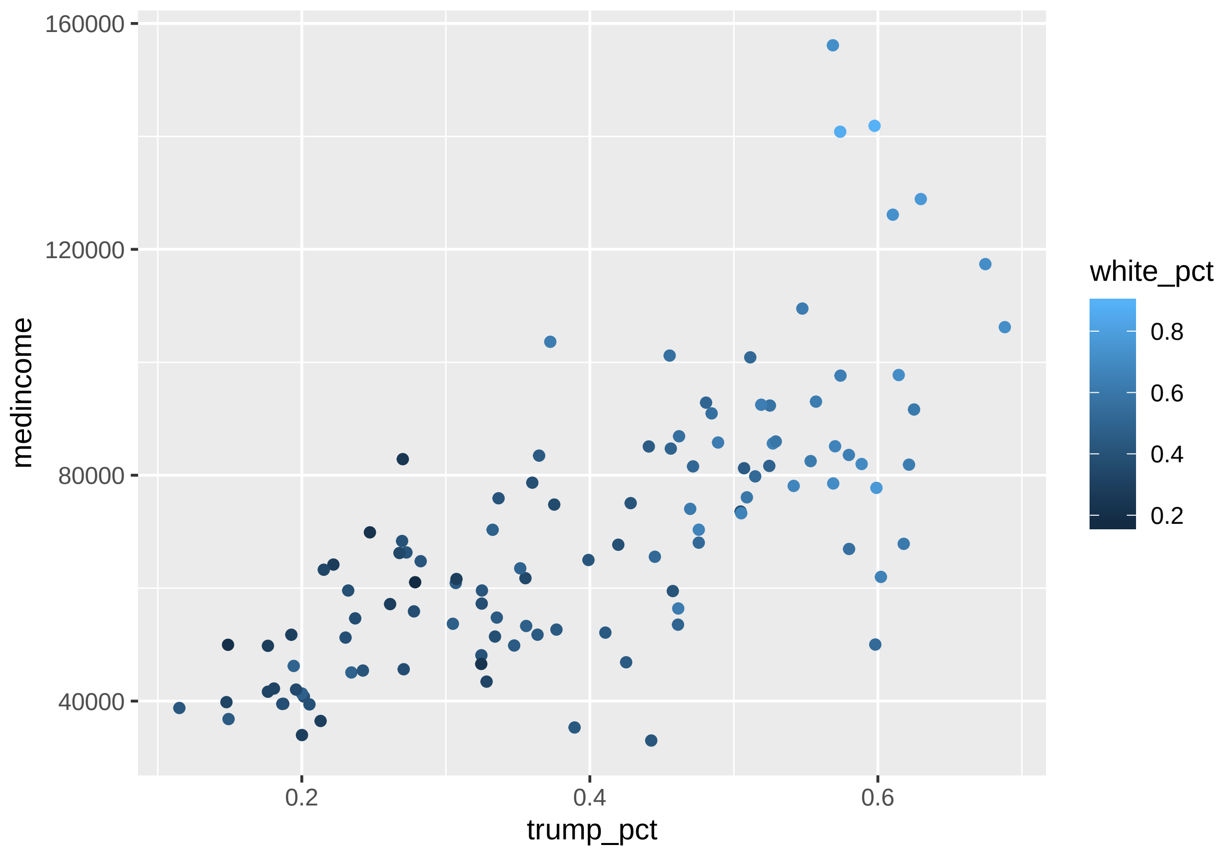
Number of Fisher Scoring iterations: 4

model 3 & 4 table

Table 4: Data-transformed regression results

	Dependent variable:	
	yes_pct	
	OLS	*logistic*
	(1)	(2)
medage	0.004**	0.015
	(0.002)	(0.075)
log_medincome	−0.008	−0.035
	(0.022)	(1.112)
white_pct	0.117**	0.563
	(0.051)	(2.560)
log_public_pct	0.022***	0.095
	(0.008)	(0.419)
time_pct	−0.281***	−1.287
	(0.090)	(4.502)
trump_pct	−0.857***	−3.647
	(0.059)	(2.960)
sqrt_voter_turnout	−0.319***	−1.458
	(0.103)	(5.216)
current_plan2	0.021	0.066
	(0.043)	(2.137)
current_plan3	−0.033***	−0.145
	(0.012)	(0.588)
current_plan4	0.014	0.048
	(0.011)	(0.568)
Constant	1.032***	2.305
	(0.219)	(10.897)
Observations	113	113
R^2	0.920	
Adjusted R^2	0.912	
Log Likelihood		−57.076
Akaike Inf. Crit.		136.153
Residual Std. Error	0.041 (df = 102)	
F Statistic	117.561*** (df = 10; 102)	
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Data-transformed linear and logistic regression results	

```r
ggplot(final_data, aes(x = trump_pct, y = medincome)) +
  geom_point(aes(colour = white_pct))
```




```r
mod5 <- lm(data = data_tf, log(yes_pct/(1-yes_pct)) ~ medage + log_medincome + white_pct + log_public_p
summary(mod5)
```

Call: lm(formula = log(yes_pct/(1 - yes_pct)) ~ medage + log_medincome + white_pct + log_public_pct + time_pct + trump_pct + sqrt_voter_turnout + current_plan, data = data_tf)

Residuals: Min 1Q Median 3Q Max -0.4368 -0.1517 -0.0092 0.1308 0.4520

Coefficients: Estimate Std. Error t value Pr(>|t|)

(Intercept) 2.432798 0.982200 2.477 0.01490 *

medage 0.014778 0.006785 2.178 0.03171 *

log_medincome -0.045983 0.100124 -0.459 0.64702

white_pct 0.630292 0.227825 2.767 0.00673 ** log_public_pct 0.090592 0.037098 2.442 0.01633 *

time_pct -1.259363 0.402697 -3.127 0.00230 ** trump_pct -3.730362 0.263039 -14.182 < 2e-16 *

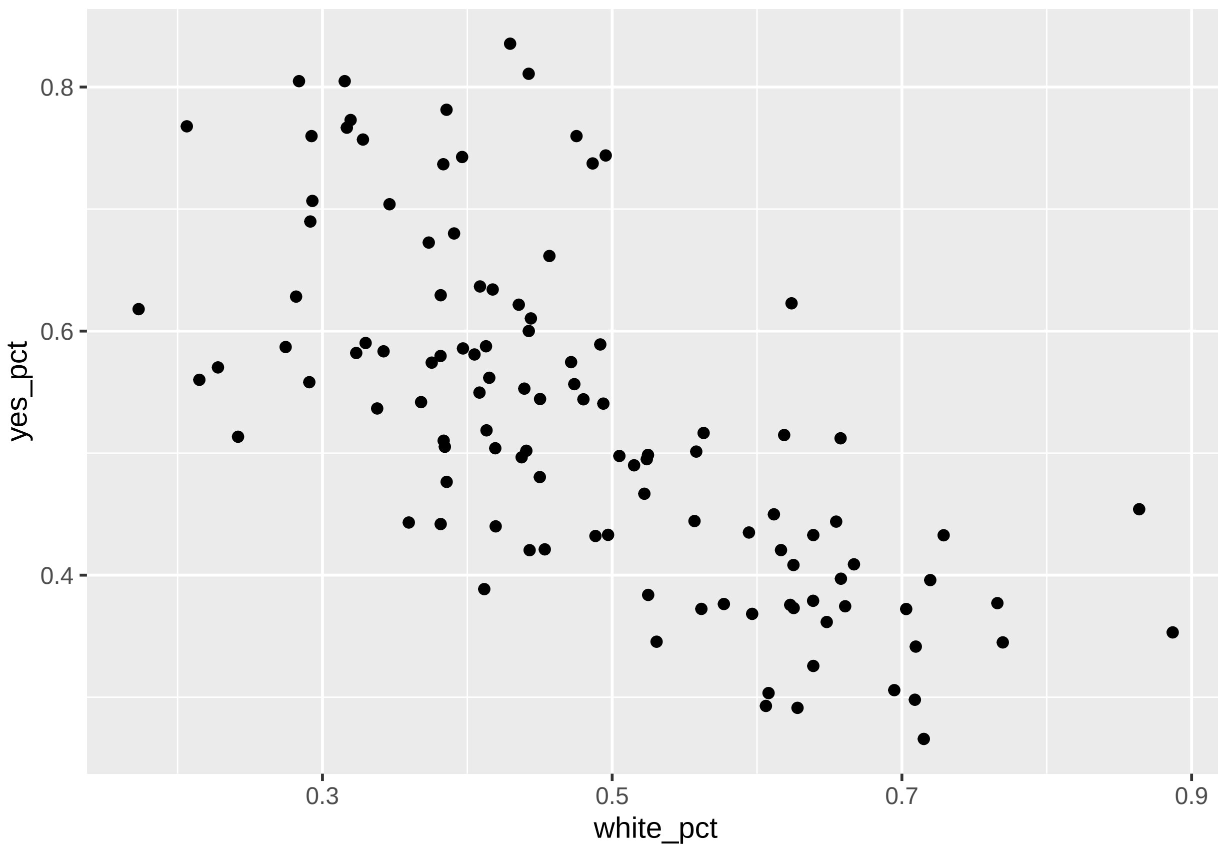
sqrt__voter__turnout -1.501691 0.464481 -3.233 0.00165 current__plan2 0.058520 0.194978 0.300 0.76468

current__plan3 -0.145459 0.052872 -2.751 0.00703 ** current__plan4 0.049736 0.051445 0.967 0.33594

— Signif. codes: 0 '***' ***0.001*** ''** *0.01* '' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1852 on 102 degrees of freedom Multiple R-squared: 0.9143, Adjusted R-squared: 0.9059 F-statistic: 108.8 on 10 and 102 DF, p-value: < 2.2e-16

```
ggplot(final_data, aes(x = white_pct, y = yes_pct))+
  geom_point()
```



5 References