Why Did Donald Trump Ofthen Call CNN News to be Fake News?*

CNN News readers significantly not willing to vote for Trump in both years of 2016 and 2020!

HAILAN HUANG

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Abstract

This study aims to investigate the question of interest that Why Did Donald Trump Ofthen Call CNN News to be Fake News? The source data used in this study is the 2020 US presidential election survey data released in Nationscape on June 25, 2020. This study used logistic model to investigate the effects of CNN news in supporting Trump for both yeas 2016 and 2020. It was found that in both years, after controlling the covariates like age, income, race and gender, CNN news readers are about over 67% lower times in odds of supporting Trump compared with that for CNN non-readers.

Contents

*Code and data are available at: https://github.com/gloriakiki/projfinal.

Keywords: US Election; Donald Trump; CNN News; Logistic Regression

1 Introduction

People always heard “This is CNN, Fake News next. Thank you much!” from Donald Trump. Donald Trump called CNN news to be “Fake News” in many public situations in this president period in the past years. Most recently, Donald Trump Jr., the eldest son of former US President Donald Trump, posted a video of a black man carrying a coffin on his personal Twitter account on April 22. In the video, the word “cnn +” is placed in the middle of the coffin with the title “celebrating cnn +.” Clearly, the Donald Trump has same mood with his son.

It is known that the United States is a big news media power country, the news media and public audio-visual have been called the fourth power beyond “legislative, judicial and executive.” And many media are divided into different factions according to their political positions, which can be roughly divided into liberal and conservative media. Cnn is a liberal media in the United States, which is called “white leftist media.” During the 2016 election, cnn was ridiculed by people as “Hillary Clinton media.” It is normal that the reports of the White House are targeted negative reports from CNN. In countries like USA, the conservative media Fox News Network has fought a big fight, This kind of power is protected by the

Constitution and cannot be deprived of public power. therefore, the freedom of the press in the United States has always been at the forefront of the world. Full-time media reporters follow up on government scandals, revelations and social injustices. These journalists themselves have a high degree of professionalism and sense of justice. When they investigate and interview politicians, they often ask sensitive issues directly. When Donald Trump faced with negative reports, he would always say "CNN, Fake News."

This study is important because social media like CNN, Facebook, Twitter, Fox are studied by lots of researchers and most of researchers pointed out that social media could affect the election outcome of US election seriously. Harder, Sevenans, and Van Aelst (2017) discussed the problem that how traditional players dominate the election times using news. Allcott and Gentzkow (2017) pointed out directly that there were lots of social media and fake news in the 2016 US election. Groshek and Koc-Michalska (2017) claimed similarly that news could help some part in election win. Based on the above backgroud, this study would also aims to investigate whether people read CNN news could affect the willingness of vote for Trump in US elections. If strong evidence founded, then it means that it is reasonable that Trump disgust CNN news and social media like CNN could indeed affect the outcome of US election seriously. This would suggest the next US candidates in future election should focus more on social media to earn as much as possible favors from voters.

The study is organized as following: first, data section introduced the source of data, the survey sampling and explory analysis results. Second, model section introduced logistic regression model and how it can be used in this study. Third, the results section show related outputs and results from model estimates. At last, conclusion and discussion sections would describe the results and give discussions of the study including strengths and limitations. The study is performed based on R (R Core Team (2020)), Rmarkdown (Allaire et al. (2021)); data cleaned by tidyverse (Wickham et al. (2019)), dplyr (Wickham et al. (2021)); plots generated by ggplot2(Wickham (2016)), scales (Wickham and Seidel (2020)), gridExtra (Auguie (2017)), ggthemes(Arnold (2021)); tables generated by broom (Robinson, Hayes, and Couch (2021)), knitr (Xie (2021)), gtsummary(Sjoberg et al. (2021)).

2 Data

The data used in this study is the 2020 US presidential election survey data released in Nationscape on June 25,2020.We use these data for Logistic regression analysis to study the effect of variables on voting results. It is well known that age-class differences will play an important role in the US presidential election because people of different ages have different needs, different policy interpretations, different ways of thinking and concerns.As a result, American political parties with different policies will have different preferences.Generally, age can be divided into four groups, most of studies use this classification: 18-34,35-50,51-65, and 65 years old. At the same time, men are always more conservative than women because their needs are often different from women.For example, differences in fertility policy can directly lead to female bias, while men may not care too much, and voters with different income levels will have different wishes to vote.We know that there are clear differences in voting behavior between the rich and the poor, this study uses a cutoff of 39999 dollars one year to divide them which is about the average level in US. Preferential policies are generally supported for the rich and better benefits for the poor.Therefore, on the basis of the above study, age, sex, race and income were selected as explanatory variables.Of course, whether to read the CNN news is also included which is the main independent variable itnerested in this study. Dummy binary variable was created in the survey data based on the variable voting results. Donald Trump is encoded as 1 against Hillary Clinton which is encoded as 0 in 2016 and Biden which is encoded as 0 in 2020.

The Survey data used in this paper are obtained from the Democracy Foundation + UCLA National Landscape (Tausanovitch and Vavreck (2020)). The access to these data is a sampling survey method using stratified sampling to organize and classify potential voters based on basic characteristics such as age, gender, race and income.The total population of this survey was that of all persons living in the United States who are voters.The sampling frame of this survey was to divide potential voters into different groups by age, sex, race, and income, and then obtain data from each group.The sample of this survey is of all American citizens involved in this survey.It should be noted that this survey was conducted online.Of the data obtained on 25 June 2020, there were over 6,000 data and nearly 260 factor variables.The application of stratified sampling is to better obtain the public opinion estimates of each group.

The Survey data should be reliable and represent a sample of the US population, as the national landscape has been trying to obtain very reliable data. A good example is the division of potential voters into stratified samples by age, sex, race, and income, followed by data from each group.Samples will be screened based on some metrics. For examples, people who answer too fast and those who answer the same question will be removed,

Of course, there are also some weakness and limitations in the survey data. First, this

Table 1: **Table 1. Summary statistics for vote 2016**

Characteristic	**0**, N = 1,915	**1**, N = 1,904
___age___		
18-34	507 / 1,915 (26%)	334 / 1,904 (18%)
35-50	567 / 1,915 (30%)	526 / 1,904 (28%)
51-65	521 / 1,915 (27%)	604 / 1,904 (32%)
65+	320 / 1,915 (17%)	440 / 1,904 (23%)
___gender___		
Female	1,130 / 1,915 (59%)	863 / 1,904 (45%)
Male	785 / 1,915 (41%)	1,041 / 1,904 (55%)
___race___		
black	412 / 1,915 (22%)	43 / 1,904 (2.3%)
other	269 / 1,915 (14%)	159 / 1,904 (8.4%)
white	1,234 / 1,915 (64%)	1,702 / 1,904 (89%)
___income___		
High	1,162 / 1,915 (61%)	1,298 / 1,904 (68%)
Low	753 / 1,915 (39%)	606 / 1,904 (32%)
___cnn___	1,147 / 1,915 (60%)	615 / 1,904 (32%)

is an online voting option.We don't know who is doing the investigation.Probably people from other professional platforms, not the voters themselves.It is also possible that voters themselves missed online voting time or did not answer questions at all, resulting in a selection bias. Secondly, too much questionnaire design may lead to answer fatigue, untrue voters' answers, and wrong choice of personal views.Finally, the stratification process can also lead to selection bias, and some layers may not be selected or have insufficient data. At last, we need to note that the outcome of voting willingness in the year 2020 is a survey response not like the one in the year 2016 which is the true outcome, however, they should be highly consistent.

Tables 1 and 2 show the summary statistics for the variables grouped by voting for Trump or not for both years 2016 and 2020. The tables show that in both 2016 and 2020, the percentages of age groups are similar which are vary around 25%, 65+ has little lower 17%

Table 2: **Table 2. Summary statistics for vote 2020**

Characteristic	**0**, N = 2,591	**1**, N = 2,212
___age___		
18-34	891 / 2,591 (34%)	502 / 2,212 (23%)
35-50	685 / 2,591 (26%)	642 / 2,212 (29%)
51-65	619 / 2,591 (24%)	648 / 2,212 (29%)
65+	396 / 2,591 (15%)	420 / 2,212 (19%)
___gender___		
Female	1,523 / 2,591 (59%)	1,053 / 2,212 (48%)
Male	1,068 / 2,591 (41%)	1,159 / 2,212 (52%)
___race___		
black	506 / 2,591 (20%)	68 / 2,212 (3.1%)
other	409 / 2,591 (16%)	212 / 2,212 (9.6%)
white	1,676 / 2,591 (65%)	1,932 / 2,212 (87%)
___income___		
High	1,505 / 2,591 (58%)	1,389 / 2,212 (63%)
Low	1,086 / 2,591 (42%)	823 / 2,212 (37%)
___cnn___	1,505 / 2,591 (58%)	673 / 2,212 (30%)

in the year 2016. For males and females, the percentages are all around 40-60%. The major differences are race that the whites have over 60% in 2016 and 89% for 2020. Also, high income level voters are about over 60% which is more than low income level. At last, CNN readers is about 60% in 2016 but only 32% for 2020 data, this is caused by the data cleanning procedure that not all data were kept in 2016 and 2020, also, not all observations are the same kept for 2016 and 2020.

Figure 1 shows the Percentage of Trump vote in 2016 and 2020 grouped by age and CNN, clearly, in both 2016 and 2020, voters not use CNN have clearly higher percentages of voters for Trump among all different age groups. The 65+ has a very high ratio to support Trump.

Figure 2 shows the Percentage of Trump vote in 2016 and 2020 grouped by gender and CNN, clearly, in both 2016 and 2020, voters not use CNN have clearly higher percentages of voters for Trump between both males and females. Males have a higher ratio support for Trump

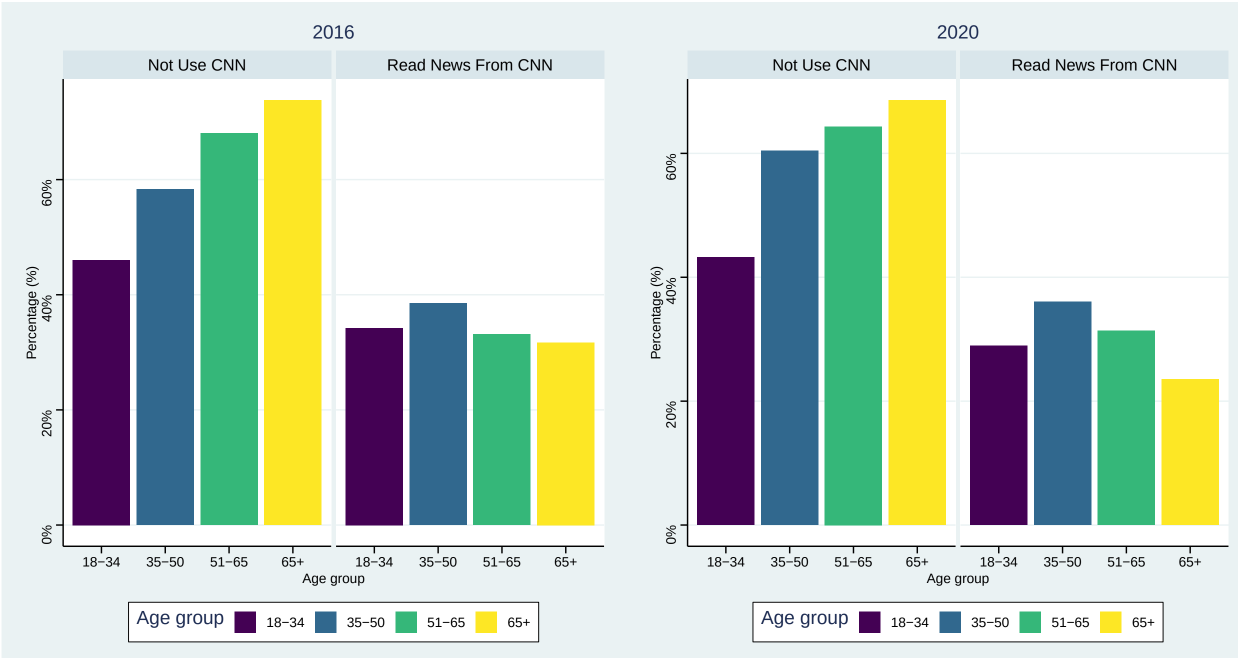


Figure 1: Percentage of Trump vote in 2016 and 2020 grouped by age and CNN

overall.

Figure 3 shows the Percentage of Trump vote in 2016 and 2020 grouped by race and CNN, clearly, in both 2016 and 2020, voters not use CNN have clearly higher percentages of white voters for Trump and moderate higehr amount for other group, for blacks, the support ratios are all low.

Figure 4 shows the Percentage of Trump vote in 2016 and 2020 grouped by income level and CNN, clearly, in both 2016 and 2020, voters not use CNN have clearly higher percentages of voters for Trump for both high and low income level voters in years 2016 and 2020.

Thus, overall, among all subgroups grouped by age, income and gender, it seems voters not use CNN have clearly higher percentages of voters for Trump in both 2016 and 2020. This indicates CNN news indeed lower the support ratio of Trump in elections.

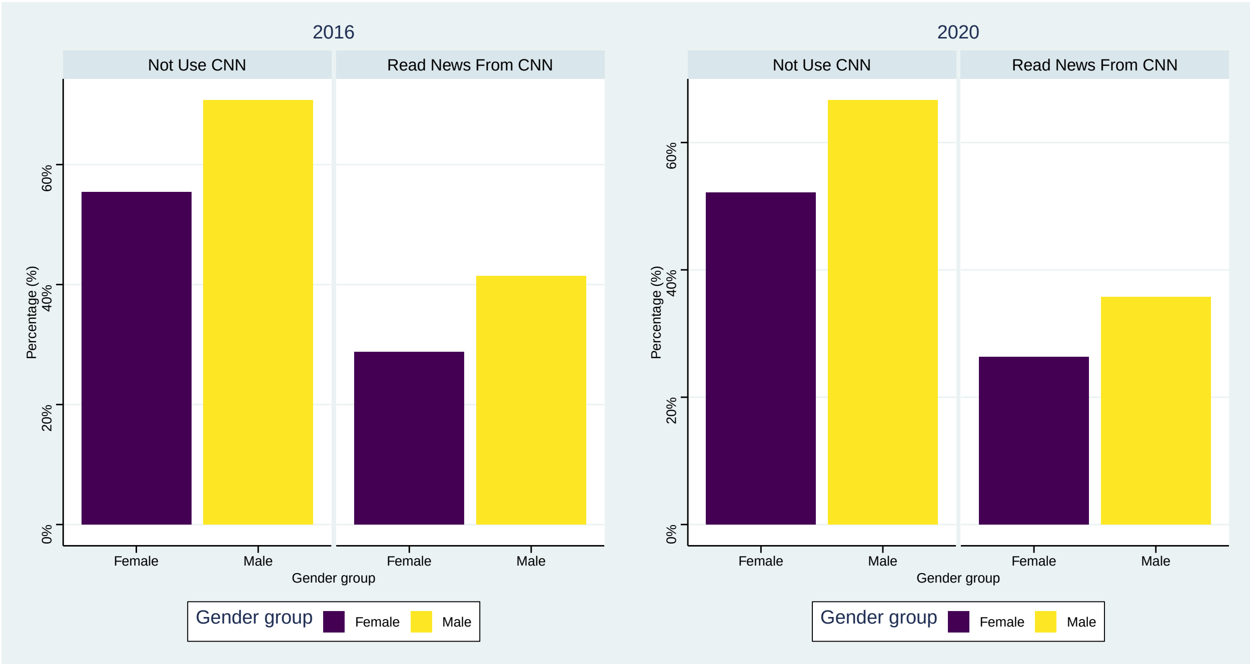


Figure 2: Percentage of Trump vote in 2016 and 2020 grouped by gender and CNN

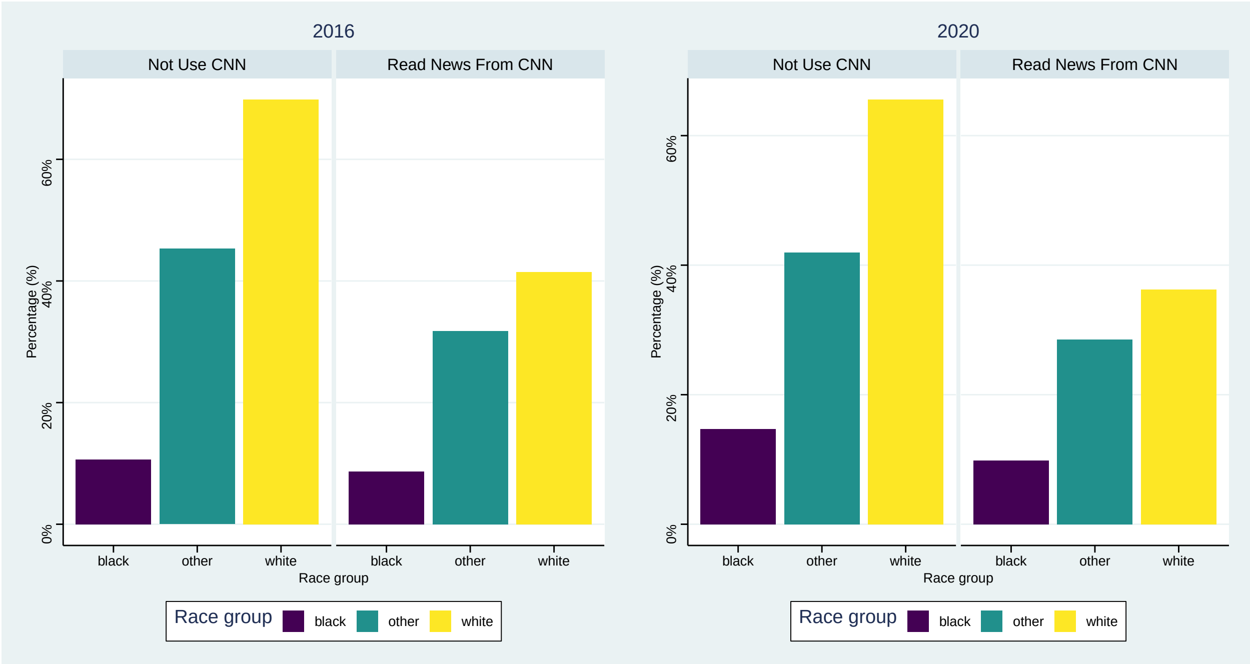


Figure 3: Percentage of Trump vote in 2016 and 2020 grouped by race and CNN

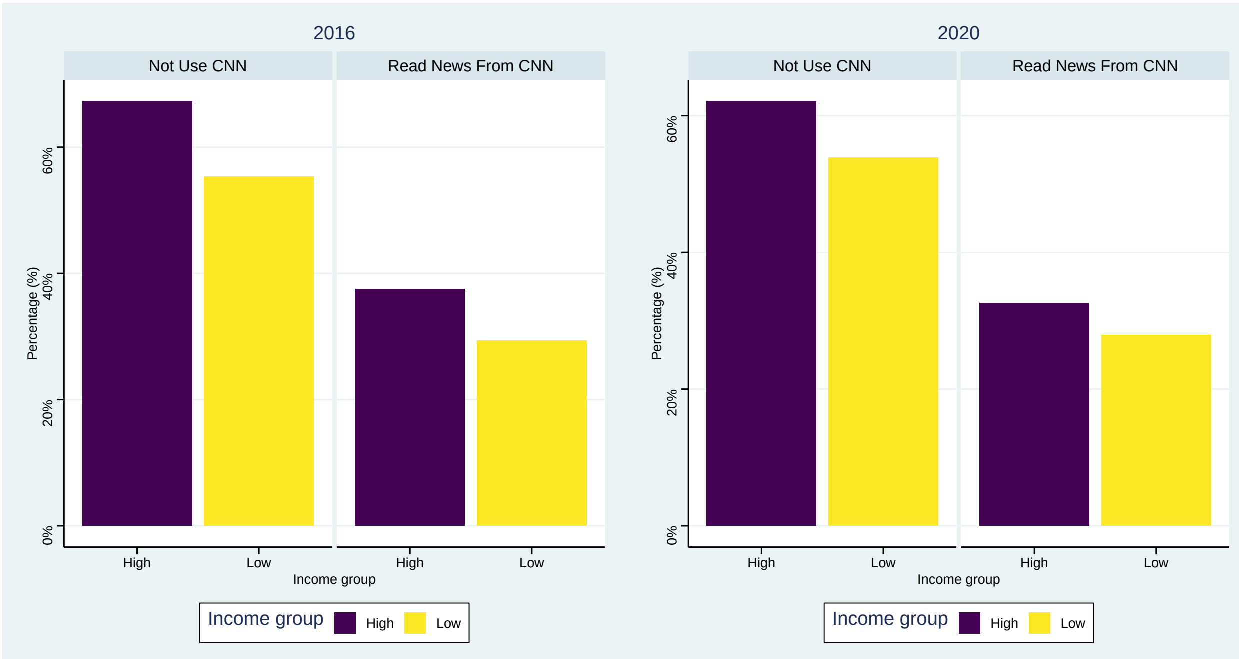


Figure 4: Percentage of Trump vote in 2016 and 2020 grouped by income and CNN

3 Model

In this paper, we use the method of logistic regression to study the problem that this study are interested in. The logistic regression method is similar to the linear regression method for fitting data, the similar thing is that the right side of the equation is a linear combination of independent variables and Coefficients, but the difference is that the link is a logical function for logistic regression while for linear model it is just the identity response variable, so logistic regression is different from linear regression, and its residuals do not need normal distribution.

The method of logistic regression has a wide range of applications, its advantages are: fast training speed, easy to understand, good interpretability of the model, suitable for two classification problems. The disadvantages are: Logistic regression can not solve the non-linear problem and is sensitive to multi-collinear data; sometimes the results of two classifications of dependent variables are not balanced and it is difficult to solve the problem of data imbalance; when the accuracy is not very high, it is difficult to fit the data well.

The main reason for using it in this paper is that it is suitable for the binary classification problem based on whether vote for Trump or not, and the model is interpretable. Due to there is no serious issues in the imbalance problem and there is no big issue in the multi-collinear data problem, so the fitting results are relatively acceptable for the classification results of dummy outcomes for voters whether Trump or other candidate is voted.

The form of the equation of logistic model is shown as below in (1):

$$log(\frac{prob}{1-prob}) = \beta_0 + \beta_1 age + \beta_2 gender + \beta_3 income + \beta_4 race + \beta_5 \text{read CNN news or not} + \epsilon \tag{1}$$

The prob in this model is the probability of voting for Donald Trump, η_0 is the intercept, and the Coefficients to estimate are β_p where p is larger than 1. The actual model results will be expanded to more than five coefficients because of age and race, as multiple categories will be divided into multiple dummy variables.

Also, note that the logit link is as following:

$$log(\frac{prob}{1-prob}) \tag{2}$$

which is a S-shape not like the linear regression model or linear probability model.

In this study, we established the above model (1) based on (Tausanovitch and Vavreck

(2020)) data, and then observed the valand significance of the estimated coefficients of each variable. The formula (1) shows the form of the logical model used. It is appropriate to use the logical model in this article, because for the final outcome of the presidential election, we produce only two people, whether Hillary Clinton or Biden Donald Trump in 2016 or 1 in 2020.

Although, different competitors may have different competencies, and there may be some bias in the model's results, namely that the data variables for 2016 and 2020 do not differ in the sense of voting for Donald Trump. However, this article is more concerned with whether CNN's influence is significantly negative based on the current election, so this issue would not affect the purpose and results of this article. Since residuals do not require a normal distribution, but rather independence, we certainly assume that the voters'results are independent of each other. However, this assumption is already confirmed when the data are obtained.

4 Results

All reference groups in the models shown in tables 3 and 4 are the group which is aged 18-34, females, blacks and high income level who not read CNN news. This because the model would create dummies for groups of categorical variables, when there is n group of catogircal variable, there are n - 1 related dummies. For examples, age group has been divided into 4 groups: 18-34, 35-50, 51-65 and 65+, then we have 3 dummies shown for 35-50, 51-65 and 65+ groups, the group 18-34 is used as baseline. For all categorical variables, the model did similar things.

Table 3 shows the Logistic model estimates for vote in 2016, the estimates are log-odds. It shows the 95% Confidence intervals (CI) for the related log-odds too. Clearly, whether a term is significant determined by whether CI contains 0 or not. The table 3 shows age35-50 is not significant while all other estimates are significant with log-odds significantly different 0. This means fixed others, age 35-50 is not significantly different from age 18-34 group in supporting Trump. The table 3 shows age 51-65 group is about 24% times (exp(0.218) -1) higher in odds of voting for Trump compared with 18-34 group fixed others. Age 65+ group is about 31.8% times (exp(0.276) -1) higher in voting for Trump compared with 18-34 group fixed others. Males is about 68.0% times (exp(0.519) -1) higher in voting for Trump compared with females fixed others. Whites and Other groups are over 5-10 times higher in in voting for Trump than blacks, the low income is about 19.3% lower in voting for Trump than blacks (1- exp(-0.215)). More importantly, CNN readers are about 66.8% (1-exp(-1.104)) lower in supporting Trump than CNN non-readers. Figure 5 shows the results from table 3 directly, clearly, we can find significant variables by observing variables whose error bars do not include 0s.

Table 4 shows the Logistic model estimates for vote in 2020, it is similarly with the table 3, except it is for the year 2020, this study assumes the responses can stand for their true willingness. Table 4 shows age35-50 is now significant while income low or high is not significant with log-odds does not significantly different 0. This means fixed others, age 35-50 is significantly different from age 18-34 group in supporting Trump with about . The table 4 shows age 51-65 group is about 45.9% times (exp(0.378)-1) higher in odds voting for

Table 3: Logistic model estimates for vote in 2016

term	estimate	std.error	statistic	conf.low	conf.high
(Intercept)	-1.921	0.185	-10.376	-2.295	-1.568
age35-50	0.140	0.103	1.367	-0.061	0.342
age51-65	0.218	0.103	2.117	0.016	0.420
age65+	0.276	0.113	2.438	0.054	0.499
genderMale	0.519	0.072	7.202	0.378	0.660
raceother	1.768	0.194	9.106	1.395	2.158
racewhite	2.366	0.169	14.017	2.047	2.710
incomeLow	-0.215	0.076	-2.815	-0.365	-0.065
cnn	-1.104	0.073	-15.123	-1.247	-0.961

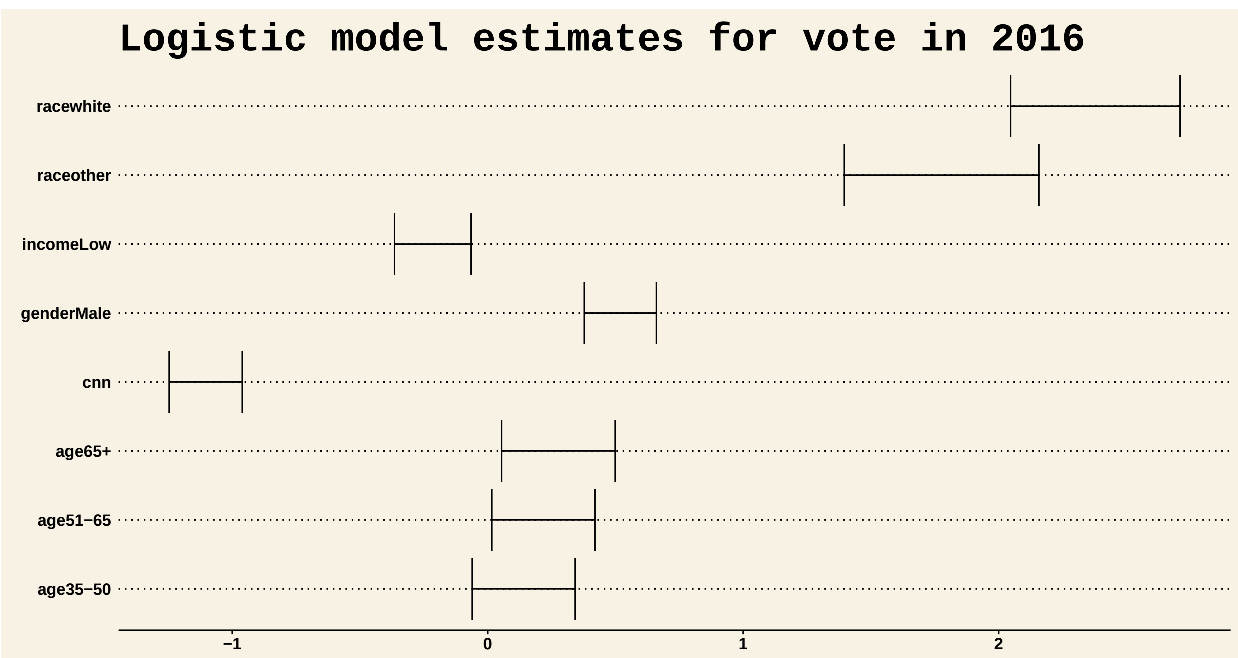


Figure 5: Logistic model estimates for vote in 2016

Table 4: Logistic model estimates for vote in 2020

term	estimate	std.error	statistic	conf.low	conf.high
(Intercept)	-1.778	0.150	-11.874	-2.078	-1.491
age35-50	0.378	0.085	4.428	0.211	0.545
age51-65	0.339	0.087	3.911	0.169	0.509
age65+	0.237	0.098	2.419	0.045	0.429
genderMale	0.436	0.064	6.832	0.311	0.561
raceother	1.405	0.159	8.828	1.098	1.723
racewhite	1.964	0.137	14.289	1.701	2.241
incomeLow	-0.101	0.066	-1.531	-0.229	0.028
cnn	-1.126	0.065	-17.391	-1.253	-1.000
CNNRead News From CNN	NA	NA	NA	NA	NA

Trump compared with 18-34 group fixed others. Age 51-65 is significantly different from age 18-34 group in supporting Trump with about 40.3% higher in odds(exp(0.339)-1). Age 65+ group is about 26.7% times (exp(0.237)-1) higher in voting for Trump compared with 18-34 group fixed others. Males is about 54.7% times (exp(0.436) -1) higher in voting for Trump compared with females fixed others. Whites and Other groups are over 3-6 times higher in in voting for Trump than blacks, the low income is about 9.6% lower in voting for Trump than blacks (1- exp(-0.101)). More importantly, CNN readers are about 67.6% (1 - exp(-1.126)) lower in supporting Trump than CNN non-readers. Figure 6 shows the results from table 4 directly, clearly, we can find significant variables by observing variables whose error bars do not include 0s.

Compare the results from both tables 3 and 4, the major differences are the significances of age 31-50 group and income high level, all other variables' effects are almost consistent between the years 2016 and 2020. More importantly, both years show after controlling the other variables, CNN readers are about over 67% lower times in odds of supporting Trump compared with that for CNN non-readers.

Due to the study aims to answer the question of interest that Why Did Donald Trump Ofthen Call CNN News to be Fake News? The hypothesis for this study is that CNN readers are not less likely in supporting Trump compared with CNN non-readers.

Based on the above results, this study rejects the null hypothesis and conclude that CNN readers are less likely in supporting Trump compared with CNN non-readers after controlling other factors.

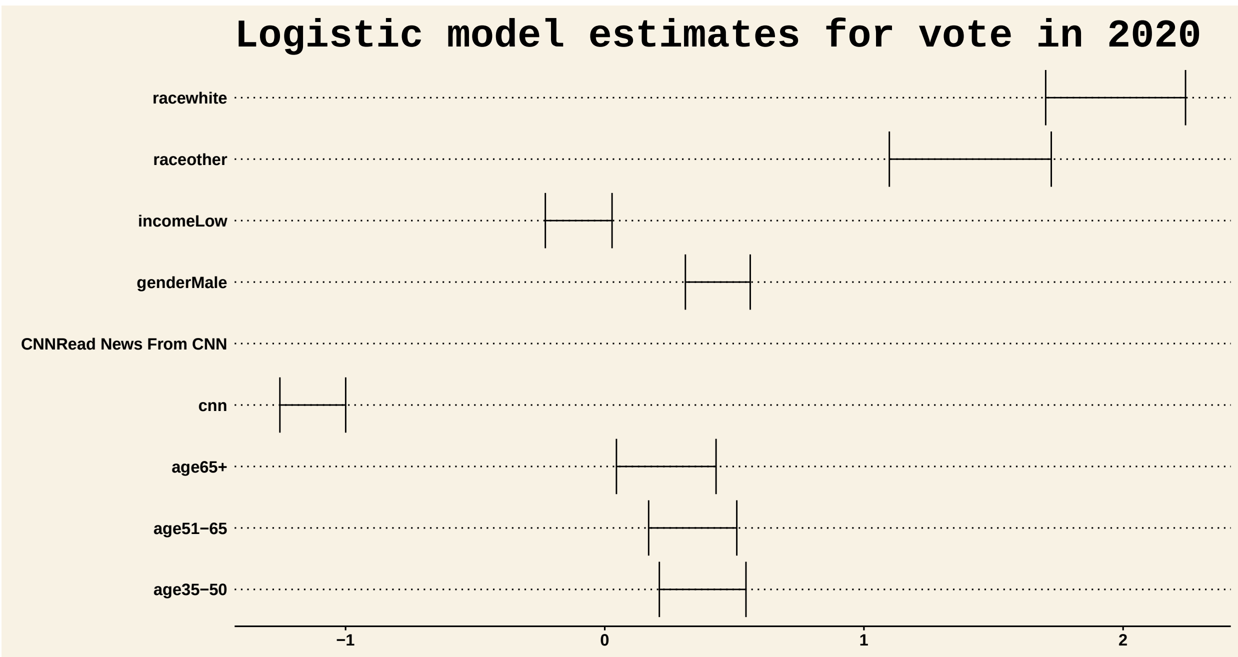


Figure 6: Logistic model estimates for vote in 2020

5 Discussion

5.1 Findings

After the study, the main findings were for Donald Trump according to the EDA findings that voters who did not appear to use CNN for all subdivided ages, income, and gender show higher supporting rates in both 2016 and 2020. This suggests that CNN News did lower Donald Trump's popularity in the election. The study is designed to answer an interesting question: Why did Donald Trump call CNN News a fake? The research hypothesis is that CNN readers are no less likely to support Donald Trump than non-CNN readers. Based on model estimates, the study rejected the null hypothesis and concluded that CNN readers were less likely than non-CNN readers to support Donald Trump after controlling for other factors.

5.2 Convariates

First, this study finds out that older people is more likely supporting Trump, most of them are over 50. One reason may be that these old people have witnessed a different America, a great America. In their view, the United States is better and stronger than now, but they think the United States is no longer like this. The status of the United States in the world has declined, which is consistent with the slogan "make America great again" put forward by the trump campaign team from the beginning. Trump's campaign has convinced older Americans that trump can return the United States to a better and stronger era. Another important reason for Trump's support from the elderly is that one of his important commitments is what these elderly people are most concerned about: social security and medical insurance. Although other Republican candidates said that social security and health care reform scared the elderly, trump repeatedly promised that he would never receive social security and health care funds to protect the health of Americans over the age of 50.

And it is easy to understand why richer people support Trump, Trump himself is a very rish people, his policy are very beneficial for those high income level voters compared with poor ones or blacks. Trump' slogan "make America great again" is said to rich people not poor people in USA.

Next, white males are more likely to support Trump, for the past two or three decades, white American men have been immersed in political correctness and depression. In the past, equal rights for women, in particular, deprived them of many jobs that used to belong to men, another reason is the rise of China, where their proud jobs have been transferred to China or permanently shut down by the government. For example, Obama once caused white men to lose their jobs and upgrade when they shut down the coal mine. when they saw TRUMP, they seemed to see new hope. They didn't want to be white people in debt.

5.3 Comparisons between 2016 and 2020

Compare the results from both tables 3 and 4, we find that the major differences are the significances of age 31-50 group and income high level in the years 2016 and 2020, the signs of them are still the same. And compare all other variables' effects, it can be found that they are almost consistent between the years 2016 and 2020 in signs and significances. Whatever Trump's Opponent is Biden or Hillary, People who read CNN news show much lower chance in supporting Trump after controlling the other variables, the models show CNN readers are about over 67% lower times in odds of supporting Trump compared with that for CNN non-readers for both years in 2016 and 2020.

And these results are highly consistent with those found in former studies such as Lee and Cho (2022), Doucet (2018), Van Der Linden, Panagopoulos, and Roozenbeek (2020). We indeed find the CNN readers are less likely voting for Trump significantly compared with that for CNN non-readers for both years in 2016 and 2020.

5.4 Weaknesses and next steps

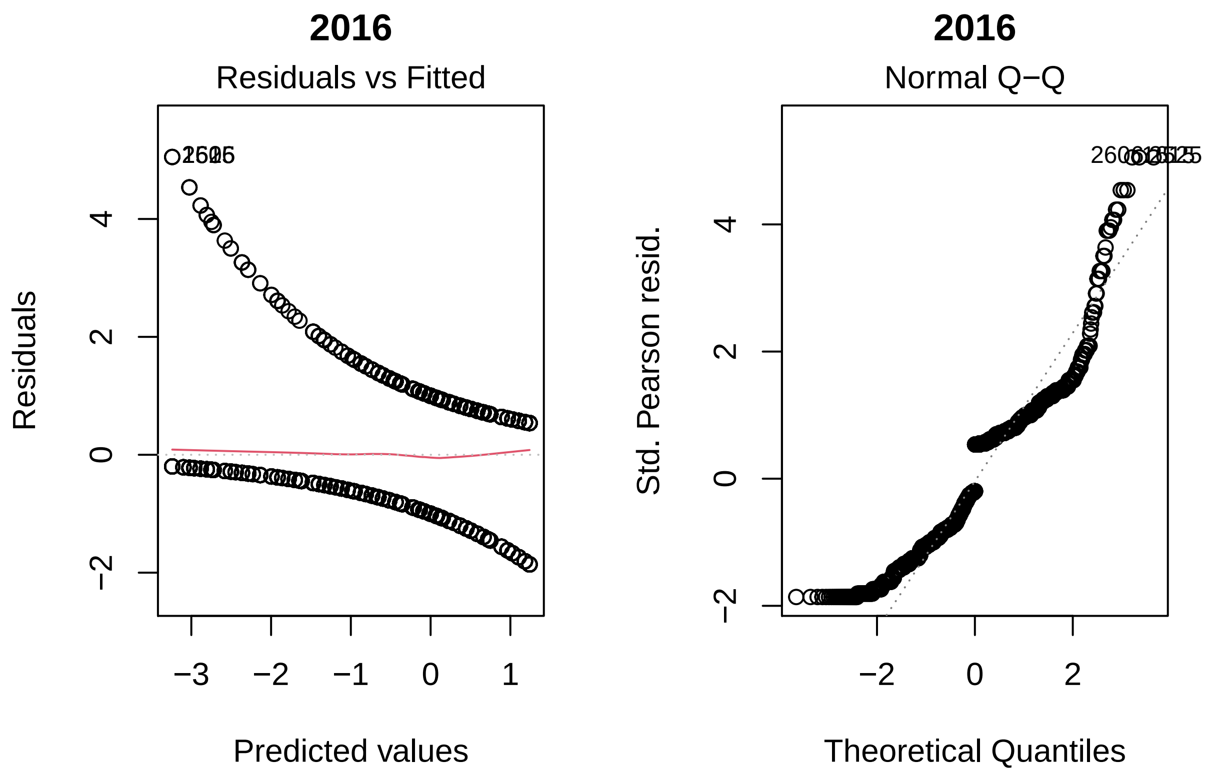
Besides all of the above findings, there are also some weakness. First, for the survey data used, as it is an online voting data. We might have selection bias in chooseing the voters. Second, there might be non-response bias as the voters might not want to answer the questions or only answer parts of questions, for some voters, after they are be selected, they just ignored the online survey or just missed to response it. Third, the survey data's response for votes in 2020 are not the true outcomes like those in the year 2016, as when the data is obtained, the 2020 election is not finished yet. Also, we might have omitted important variables bianess, this study contains basic features like age, gender, income level, race which might not be enough to estimate an unbiased effect of CNN news on Trump's election. At last, there are some non-consistency between results of 2016 and 2020 of the effects of coviarates, this might due to the data cleaning procedures leading to imblanced data sets between 2016 and 2020 which can be founded in tables 1 and 2.

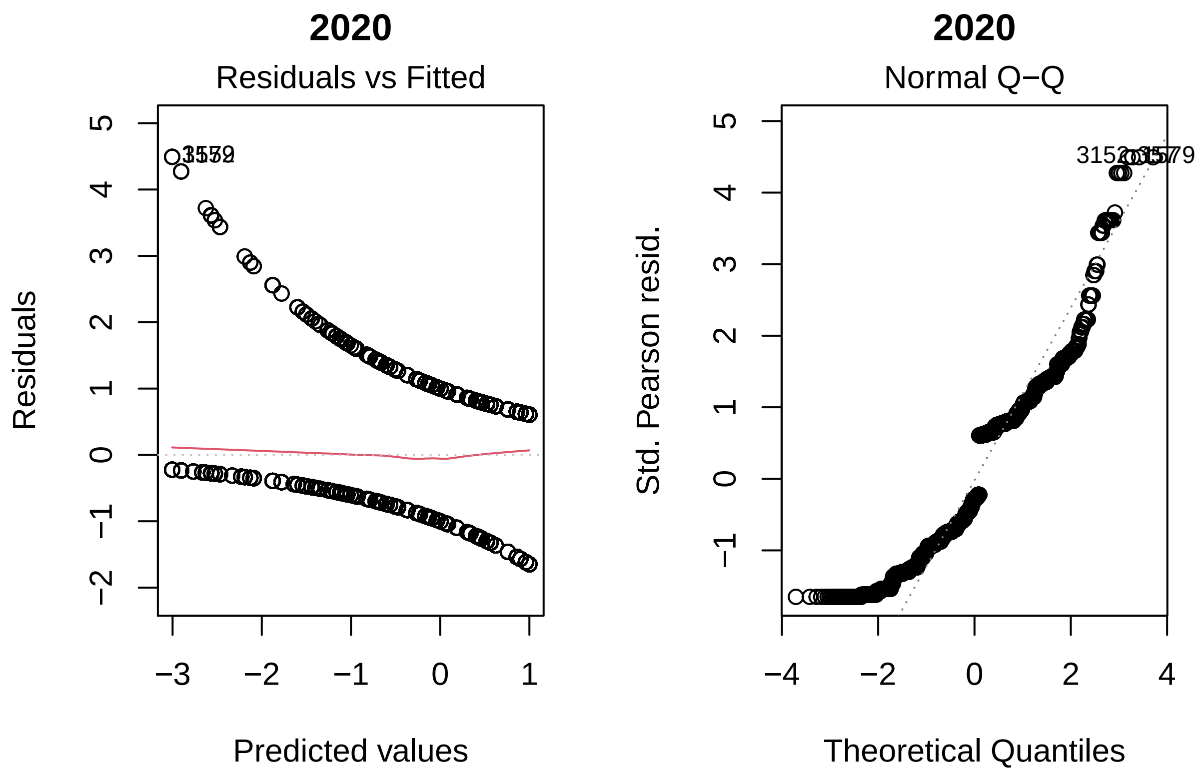
For future study, we mainly aim to solve some issues in this study. First, we might perform the data cleaning more careful and including more variables to reduce the omitted variable biasness and inconsistency between data sets in 2016 and 2020. Second, we might try to obtain a new data for 2020 outcome which is actually happened, this is some diffcult as we need same results for 2016 outcomes too. At last, we can design a self-made survey to analysis to find whether the results are consistent with the findings in this study.

Appendix

A Additional details

The model diagnostics are, no big issues are founded.




2020
Residuals vs Fitted
Residuals
Predicted values
−3
−2
−1
0
1
2
3
4
5
2020
Normal Q−Q
Std. Pearson resid.
Theoretical Quantiles
3152
3579
−4
−2
0
2
4

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