

Gender triggers the low voter turnout?*

Men are more likely to vote!

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Abstract

Observing the significant political influence of low voter turnout and huge different between the predicted results of election in polls and in real world, this paper analyses the issues of low voter turnout and aims to find people with what features are more unwilling to vote. Datasets about the 2019 Canadian Election survey are obtained, cleaned and analysed with a simple and multiple logistic regression model, with the interest of gender impact, I found that men are more likely to vote than women and others. The results and the study appeal for politicians to predict the final results of the election taking everyone's vote and thus to come up policies that call people to vote.

Keywords: Political participation, Low voter turnout, 2019 Canadian election, logistic regression

Introduction

Political participation has always been a sharp issue in the elections and low voter turnout and inequalities have significant political and policy consequences. Due to the low voter turnout, the results of public opinion poll have large gap and sometimes even huge difference from the true, final results. Eyes on the issues of low voter turnout and the difference between poll and the actual results, a question to be asked is people with what features are more unwilling to vote. In this paper, a simple logistic regression model is conducted according to the CES dataset obtained from the 2019 Canadian election in R and findings on the importance of turnout based on the model and results are discussed.

Based on the dataset, I have applied a statistical method to build one simple logistic regression model in this analysis to predict find people with what features are more unwilling to vote in 2019 Canadian election. I have learned that men are more likely to vote than women and other genders after conducting simple and multiple linear regressions.

The paper is organized in the following parts with a full disclosure and analysis of the data I used to build my study in the Data Section, some detailed discussions on the statistical models that I used for forecasting in Model Section, some discussions and results, and also some limitations and nextsteps.

Data

CES2019 online data is used in this paper. The data are obtained in Canada Election Study 2019, which is conducted online.

*Code and data are available at: <https://github.com/linziguan0118/304-Final-Project.git>

Data Variables

Variables I am using include: cps19_gender: A Categorical variable indicating self-reported gender, including a man, a woman and Other (e.g. Trans, non-binary, two-spirit, gender-queer) cps19_v_likely: A Categorical variable indicating whether or not people are willing to vote cps19_education: A Categorical variable indicating education level cps19_bornin_canada: A Categorical variable indicating whether or not the person is born in Canada

Survey methodology

The 2019 Canadian Election Study was conducted with a two-wave panel with a modified rolling-cross section during the campaign period and a post-election recontact wave.

Population, frame and sample

The target population of Canadian citizens and permanent residents who are aged 18 or older. Frame is people who can access Qualtrics and the sample is designed to be online sample with 37,822 members of the Canadian general population through Qualtrics, which targets stratified by region and balanced on gender and age within each region.

Data features and strengths

- Representativeness: The proportion of respondents are controlled and targeted to be representative: for example, 50% men and 50% women are targeted.
- Data accuracy: Duplicate variables have been removed to improve data accuracy.
- Non response: Non response answers and answers that ineligible or incomplete are removed to increase the overall accuracy.

Data weaknesses

- Imperfect coverage: The sample only considers people that can access Qualtrics, which cannot cover all the people that have the voting rights. +Sampling error: Sampling error is unavoidable. The results will vary from sample to sample. It will surely be different from the results of the true voting data.

Key facts about the data:

Overall, most people indicate that they are certain to vote in the election but there are also a number of people indicating not to vote or unlikely to vote. There are more women taking the survey than men. But there is no obvious proclivity for voting. Different education level has its own potential to voting choice. Proportion of not voting is higher for people born in Canada

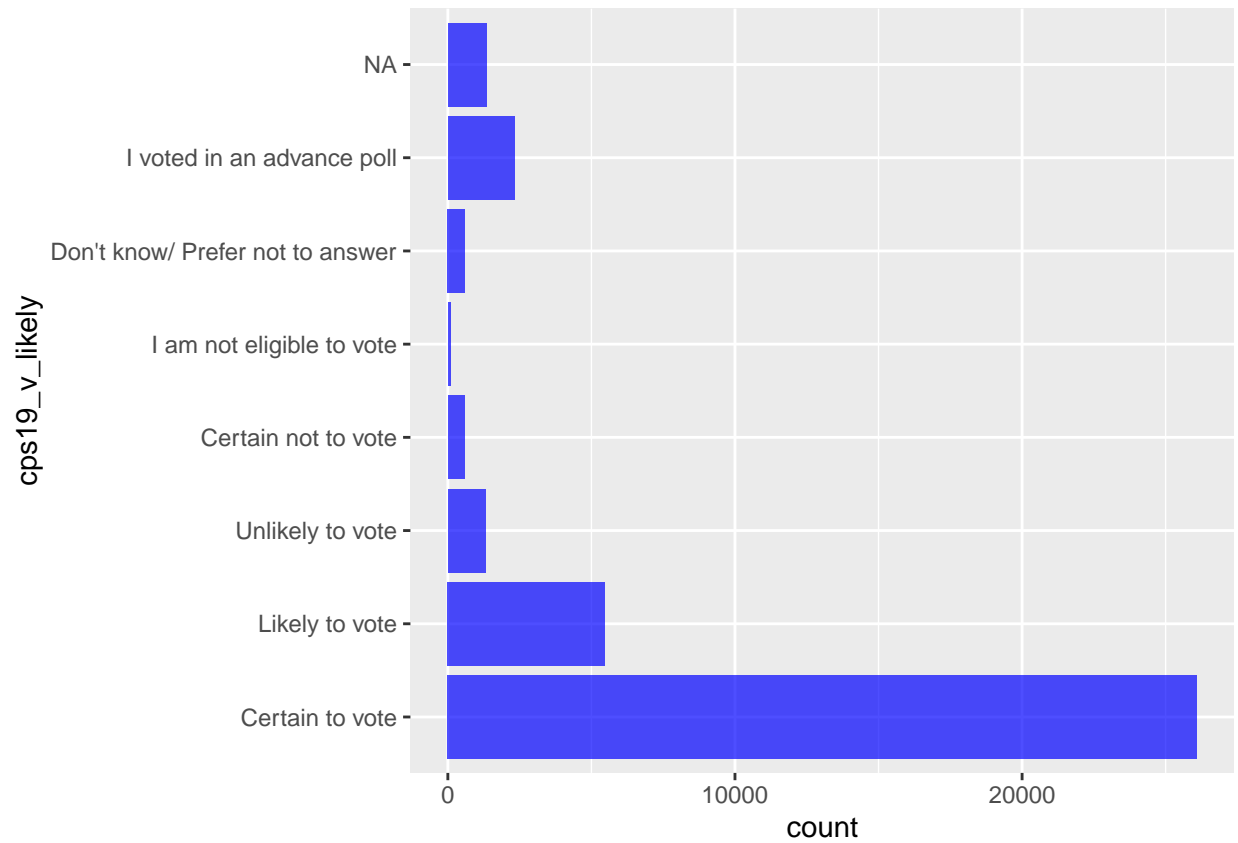


Figure 1: Voting intentions. The length of the bars represent the magnitude of number of voting people. Longer bar means larger number of votes. From the bar chart, we can find most people indicate that they are certain to vote in the election but there are also a number of people indicating not to vote or unlikely to vote.

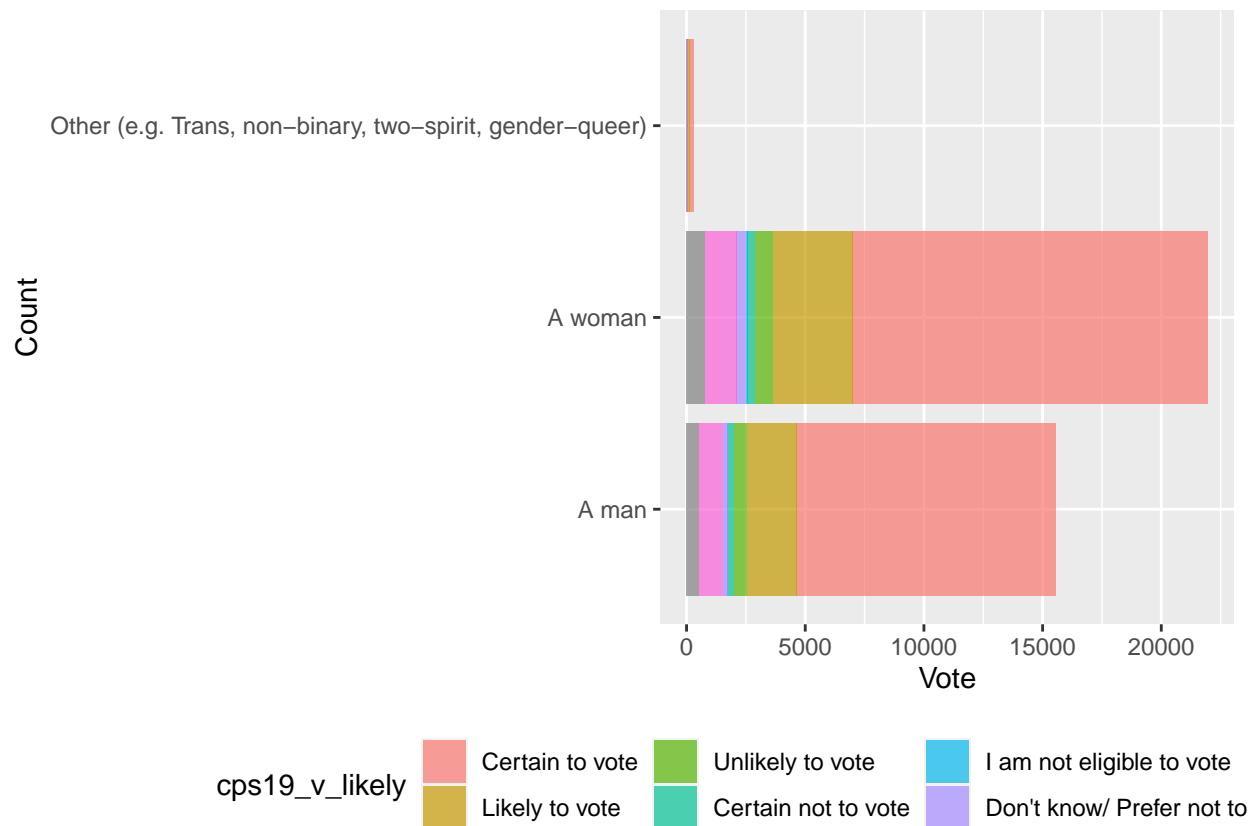


Figure 2: Voting intention counts in different gender. The colours represent different genders: red for man, green for women and blue for others. The length of the bars represent the magnitude of number of voting people. Longer bar means larger number of votes. From the bar chart, we can find here are more women taking the survey than men. But there is no obvious proclivity for voting.

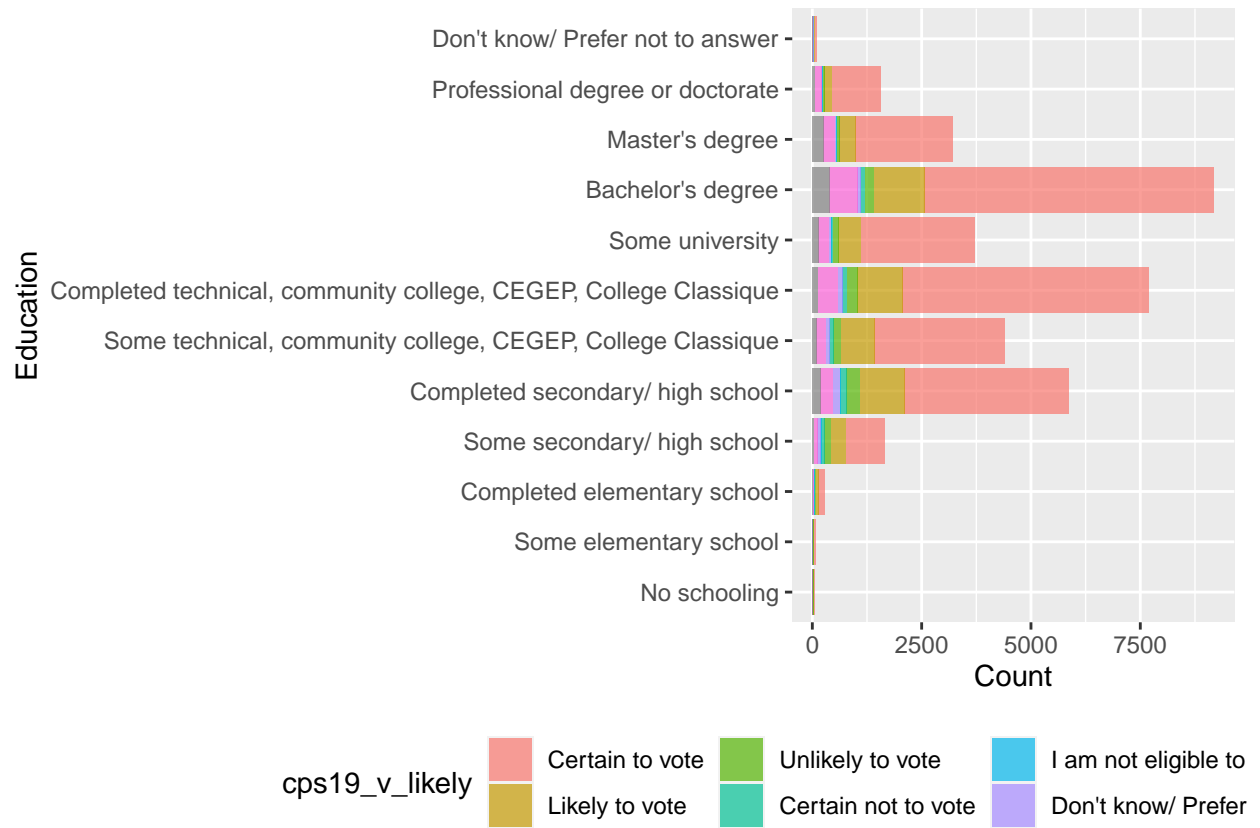


Figure 3: Voting intention counts in different education level. The colours represent different education levels. The length of the bars represent the magnitude of number of voting people. Longer bar means larger number of votes. Different education level has its own potential to voting choice.

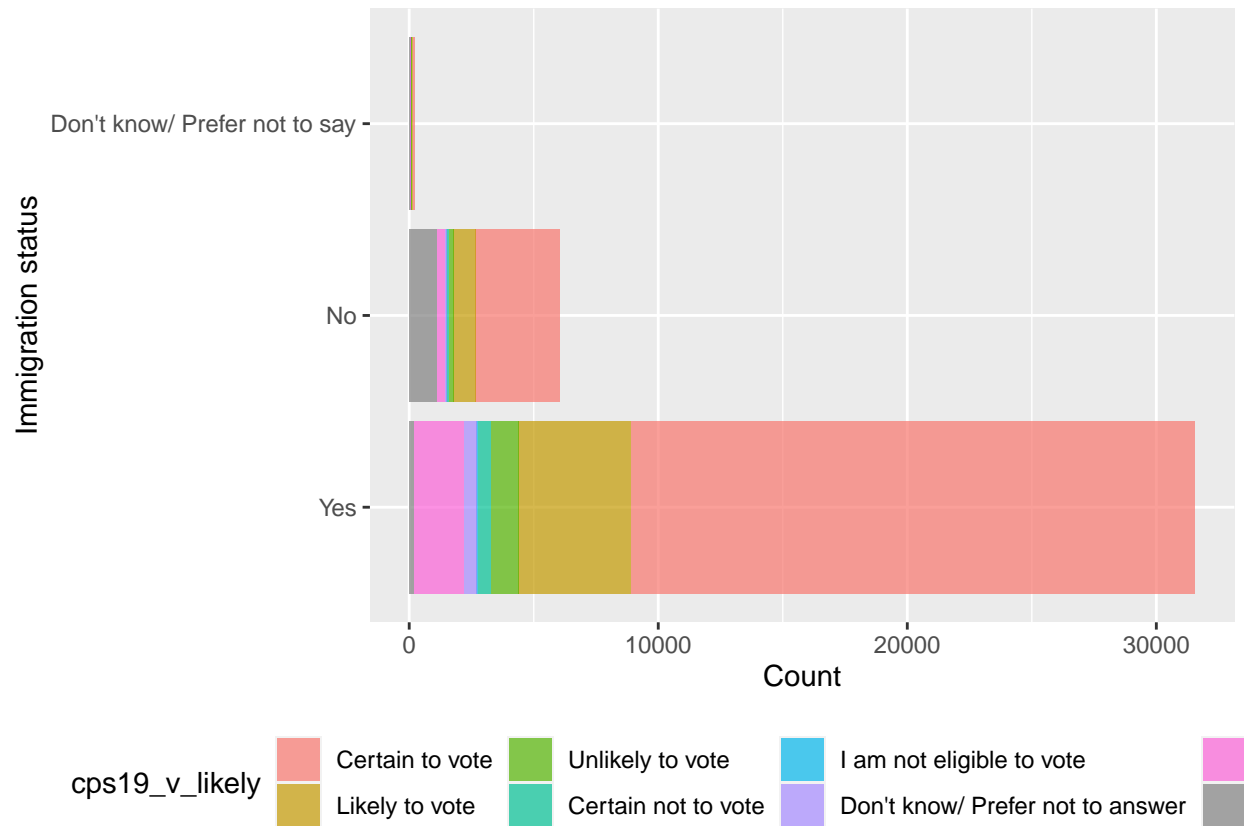


Figure 4: Voting intention counts with different immigration status. The colours represent different immigration statuses. The length of the bars represent the magnitude of number of voting people. Longer bar means larger number of votes. Proportion of not voting is higher for people born in Canada

Model

To see how gender impacts the likelihood to vote, I firstly conduct a simple linear regression model of certain to vote on gender. To improve the model, I conduct a multiple linear regression model of certain to vote on gender, after controlling education and immigration status.

Result

The result of simple linear regression of certain to vote on gender:

```
##
## Call:
## lm(formula = `cps19_v_likely_Certain to vote` ~ cps19_gender,
##     data = ces2019_web)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7273 -0.7072  0.2727  0.2928  0.3297
##
```

```
## Coefficients:
##                                     Estimate
## (Intercept)                      0.727261
## cps19_genderA woman              -0.020048
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer) -0.056971
##                                     Std. Error
## (Intercept)                      0.003682
## cps19_genderA woman              0.004813
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer) 0.027409
##                                     t value
## (Intercept)                     197.519
## cps19_genderA woman             -4.165
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer) -2.079
##                                     Pr(>|t|)
## (Intercept)                     < 2e-16
## cps19_genderA woman             3.12e-05
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer) 0.0377
##
## (Intercept)                      ***
## cps19_genderA woman              ***
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer) *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4512 on 36477 degrees of freedom
## (1342 observations deleted due to missingness)
## Multiple R-squared:  0.0005508, Adjusted R-squared:  0.000496
## F-statistic: 10.05 on 2 and 36477 DF, p-value: 4.325e-05
```

The results of multiple regression of certain to vote on gender, holding education and immigration status constant are shown below:

```
##
## Call:
## lm(formula = `cps19_v_likely_Certain to vote` ~ cps19_gender +
##     cps19_education + cps19_bornin_canada, data = ces2019_web)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7809 -0.6386  0.2449  0.2871  0.8787
##
## Coefficients:
##                                     Estimate
## (Intercept)                      0.448648
## cps19_genderA woman              -0.021923
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer) -0.052519
## cps19_educationSome elementary school      0.081245
## cps19_educationCompleted elementary school 0.137868
## cps19_educationSome secondary/ high school 0.119557
## cps19_educationCompleted secondary/ high school 0.233484
## cps19_educationSome technical, community college, CEGEP, College Classique 0.264286
## cps19_educationCompleted technical, community college, CEGEP, College Classique 0.315906
## cps19_educationSome university            0.301680
## cps19_educationBachelor's degree          0.328332
```

## cps19_educationMaster's degree	0.332289
## cps19_educationProfessional degree or doctorate	0.315716
## cps19_educationDon't know/ Prefer not to answer	0.062941
## cps19_bornin_canadaNo	-0.052426
## cps19_bornin_canadaDon't know/ Prefer not to say	-0.305389
##	Std. Error
## (Intercept)	0.069104
## cps19_genderA woman	0.004791
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer)	0.027178
## cps19_educationSome elementary school	0.084702
## cps19_educationCompleted elementary school	0.074196
## cps19_educationSome secondary/ high school	0.069959
## cps19_educationCompleted secondary/ high school	0.069332
## cps19_educationSome technical, community college, CEGEP, College Classique	0.069412
## cps19_educationCompleted technical, community college, CEGEP, College Classique	0.069272
## cps19_educationSome university	0.069479
## cps19_educationBachelor's degree	0.069243
## cps19_educationMaster's degree	0.069565
## cps19_educationProfessional degree or doctorate	0.070021
## cps19_educationDon't know/ Prefer not to answer	0.082617
## cps19_bornin_canadaNo	0.006942
## cps19_bornin_canadaDon't know/ Prefer not to say	0.032451
##	t value
## (Intercept)	6.492
## cps19_genderA woman	-4.576
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer)	-1.932
## cps19_educationSome elementary school	0.959
## cps19_educationCompleted elementary school	1.858
## cps19_educationSome secondary/ high school	1.709
## cps19_educationCompleted secondary/ high school	3.368
## cps19_educationSome technical, community college, CEGEP, College Classique	3.808
## cps19_educationCompleted technical, community college, CEGEP, College Classique	4.560
## cps19_educationSome university	4.342
## cps19_educationBachelor's degree	4.742
## cps19_educationMaster's degree	4.777
## cps19_educationProfessional degree or doctorate	4.509
## cps19_educationDon't know/ Prefer not to answer	0.762
## cps19_bornin_canadaNo	-7.552
## cps19_bornin_canadaDon't know/ Prefer not to say	-9.411
##	Pr(> t)
## (Intercept)	8.56e-11
## cps19_genderA woman	4.75e-06
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer)	0.053319
## cps19_educationSome elementary school	0.337468
## cps19_educationCompleted elementary school	0.063156
## cps19_educationSome secondary/ high school	0.087470
## cps19_educationCompleted secondary/ high school	0.000759
## cps19_educationSome technical, community college, CEGEP, College Classique	0.000141
## cps19_educationCompleted technical, community college, CEGEP, College Classique	5.12e-06
## cps19_educationSome university	1.42e-05
## cps19_educationBachelor's degree	2.13e-06
## cps19_educationMaster's degree	1.79e-06
## cps19_educationProfessional degree or doctorate	6.54e-06
## cps19_educationDon't know/ Prefer not to answer	0.446161


```
## cps19_bornin_canadaNo 4.37e-14
## cps19_bornin_canadaDon't know/ Prefer not to say < 2e-16
##
## (Intercept) ***
## cps19_genderA woman ***
## cps19_genderOther (e.g. Trans, non-binary, two-spirit, gender-queer) .
## cps19_educationSome elementary school
## cps19_educationCompleted elementary school .
## cps19_educationSome secondary/ high school .
## cps19_educationCompleted secondary/ high school ***
## cps19_educationSome technical, community college, CEGEP, College Classique ***
## cps19_educationCompleted technical, community college, CEGEP, College Classique ***
## cps19_educationSome university ***
## cps19_educationBachelor's degree ***
## cps19_educationMaster's degree ***
## cps19_educationProfessional degree or doctorate ***
## cps19_educationDon't know/ Prefer not to answer
## cps19_bornin_canadaNo ***
## cps19_bornin_canadaDon't know/ Prefer not to say ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4472 on 36464 degrees of freedom
## (1342 observations deleted due to missingness)
## Multiple R-squared:  0.01885, Adjusted R-squared:  0.01844
## F-statistic: 46.69 on 15 and 36464 DF, p-value: < 2.2e-16
```

Discussion

According to the simple model result, the adjusted R square is less than 1%, showing that less than 1% of variation in certain to vote can be explained by gender. P-value for a woman and others are both smaller than 5%, and that is to say they are statistically significant. On average, men are 0.02 more likely to vote than women and 0.06 more likely to vote than others.

With multiple regression, the adjusted R square has been improved to 2%, showing more variation could be explained by gender, holding other variables constant. P-values are both smaller than 5%, and that is to say they are statistically significant. On average, holding other variables constant, men are 0.02 more likely to vote than women and 0.05 more likely to vote than others.

Limitations and next steps

The coverage of the survey is limited so the result is not fully representative. The model does not fit that well, so next step I might use multilevel logistic regression with post stratification.

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