Biden to win the popular vote in the 2020 American presidential elections

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Abstract

"Why do/should we care about the problem and the results. What problem are we trying to solve. How did we go about solving or making progress on the problem? What is our answer? What are the implications of our answer?."

Keywords: Forecasting; US 2020 Election; Trump; Biden; Multilevel regression with post-stratification

1 Introduction

Forecasting is an integral human activity (Silver, 2012; Tetlock and Gardner, 2016) and voting is one of democracy's most important civic duties. Putting the two together, therefore, forecasting the outcome of the presidential elections in the United States of America–one of the most important democracies on the planet–is perhaps the most widely discussed prediction in all of social discourse (after the weather, of course!).

In 2008, 89% of Americans had said that they read about the latest polls in the presidential contest (Erikson and Tedin, 2015) and it is expected that that number is even higher in 2020. There are important practical considerations as to why forecasting the presidential elections is important. It is reasonable to assume that the identity of the president of the United States has an influence on the likelihood that certain state policies may be adopted during the tenure of their presidency. Thus, stakeholders throughout the world would want to know the odds of certain policies being enacted in the future in order to be best prepared to mitigate or take maximum advantage when the time comes.

In this paper, we aim to predict the outcome of the overall popular vote of the 2020 American presidential election using public opinion polling data. People have different views over whether political polling are reliable predictors of election outcomes, especially after the shock victory of President Trump in 2016 which most pollsters failed to predict. Gelman and Azari (2017) point to nineteen lessons learned from that election, most relevant to our paper of which is the lesson that one needs to be cautious of survey nonresponse bias. Kennedy et al. (2018) showed that a late swing in vote preference toward Trump, a failure to adjust for overrepresentation of college graduates who mostly favored Clinton, and a clear change in voter turnout from 2012 to 2016 were some of the main reasons why pre-election polls performed poorly in 2016. Moreover, the rise of populism in America and the resulting countermovement makes elections more unpredictable than ever (Inglehart and Norris, 2016), even with the explosion of data availability. Notwithstanding these issues, the use of public opinion polling data continues to be common practice and we make use of it in this paper. (BRIEFLY discuss datasets here).

We find that Biden/Trump is likely to win! (briefly discuss results here).

The remainder of the paper is structured as follows. Section 2 discusses the datasets that we use and describes the data cleaning process. Section 3 introduces our models and discusses the multilevel regression with post-stratification methodology that we used. Section 4 presents our results. Finally, Section 5 discusses our results, addresses limitations, and suggests future avenues for work in this area.

Introduce R, R packages used, logistic regression and MRP methods briefly here as well as a quick note on results..briefly introduce which data we use and what key findings were…WHO IS GOING TO WIN??…give a sketch of the rest of the report)

2 Data

Before going into the details of the post-stratification we conducted, we will discuss what post-stratification is and when it can be used. Post-stratification is implemented after simpler random samples have been conducted. It is used to properly balance the representation of variables across the target population to gain more precise estimates and create greater confidence in inferences being made. Post-stratification involves classifying each member of a population into a single subgroup or strata to then calculate the probability sample from each stratum. Because of this, post-stratification cannot be used in studies with observations that overlap or are not clearly classified, as this may inaccurately reflect the population. Another challenge is to find definitive lists of variables for an entire population that fall in line with the variables collected for the original sample.

The data we used to post-stratify was the 2018 American Community Survey (ACS) data which we downloaded from the Integrated Public Use Microdata (IPUMS) US project website (Ruggles et al., 2020). The ACS is a national survey that is conducted annually. Participation in the survey is manadatory by law. It supplements the census and provides annual data on information to determine federal and state funds in America (the target population). The U.S. Bureau contacts 3.5 million randomly selected American households (the sampling frame) from their master address file each year to take the standardized survey through internet, mail, telephone, or in-person interviews. These addresses are selected through a sampling method that ensures that a more stable estimate for sparsely populated areas and groups (Groves, 2012). Since the survey is mandatory, the frame and actual sample are very similar. The Census Bureau is bound to strict confidentiality and has employed statistical methodologies so that the data we have access to has no identifying information. Strengths of the ACS would be its large scale response rate and several topics covering housing, social, and economical characteristics. However, the ACS lacks other key variables such as precise household vicinity, political ideology, and religion.

While the ACS data measures hundreds of variables, we extracted 10 demographic variables we thought could predict the popular vote in the 2020 American presidential election. They were: age, sex, household income, education attainment, employment status, state, region, birthplace, race, and whether a respondent had Hispanic origins. These variables were also chosen because of their ability to coincide with that of the survey variables. For example, household income was chosen rather than individual income since the UCLA survey did not ask about personal income. We further manipulated the data by cleaning responses to match the UCLA options. For income, we constructed bins of income intervals that match the survey's since the ACS had exact income values. We selected respondents between 18 and 93 years of age. We made birthplace a binary variable to be either born in the 'USA' or 'another country'. We constructed a new race variable that incorporates Hispanic origins; this meant that if a respondent had answered they had Hispanic origins, it would override and replace the answer of their identifying race. We also kept Chinese identifying respondents separate from other Asians and did these things because Chinese and Hispanic respondents have shown to have strong voting trends with contemporary topics like America's border policies and COVID-19 (Krogstad and Lopez, 2020). The figure below depicts the variables of the ACS data after cleaning.

3 Model

4 Results

5 Discussion, Limitations, and Future Work

Insert comment here from Kennedy and Gelman (2019, p. 19) about cost/benefits of MRP.

"Given the bias in the survey, discussed in Data section, we used MRP to. . . . . . While this would address some aspects of the bias [discuss bits that it can address], it cannot address all of it. This includes [discuss bits that it cannot address]."

Our model assumed people would either vote for Trump or Biden. In reality, independent voters would also. . . so. . . Multinomial logistic regression model would be more appropriate.

Due to the unavailability of variables in the post-stratification data, we were not able to use important survey questions pertaining to attitudes and behaviors of voters towards policies and contemporary issues. Policies that are of concern to voters are known to influence voter choice (Petrocik, 1996). Some beliefs and attitudes might be correlated with certain demographic variables which we used, and may have helped in

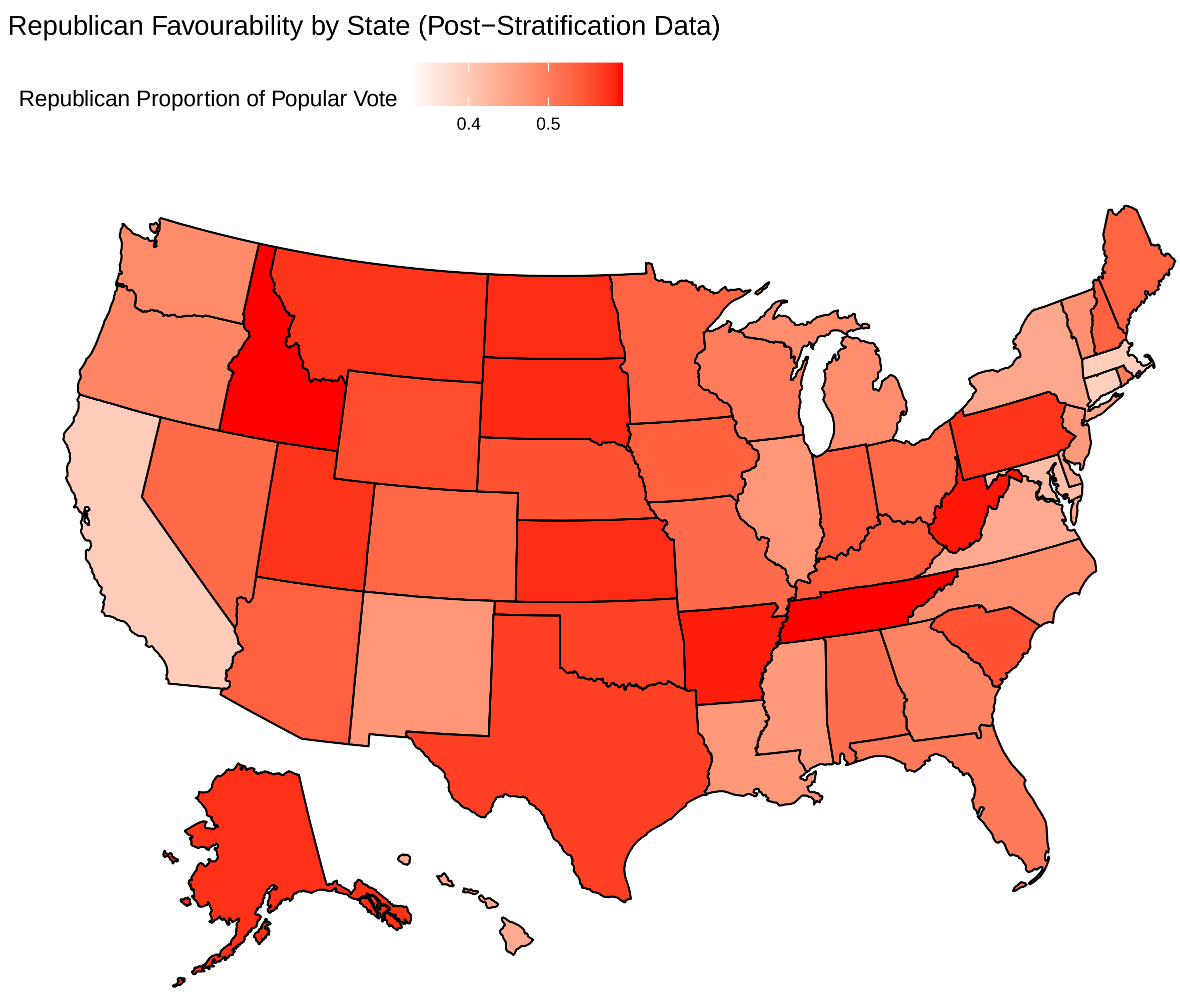

Figure 1: Trump favorability by state.

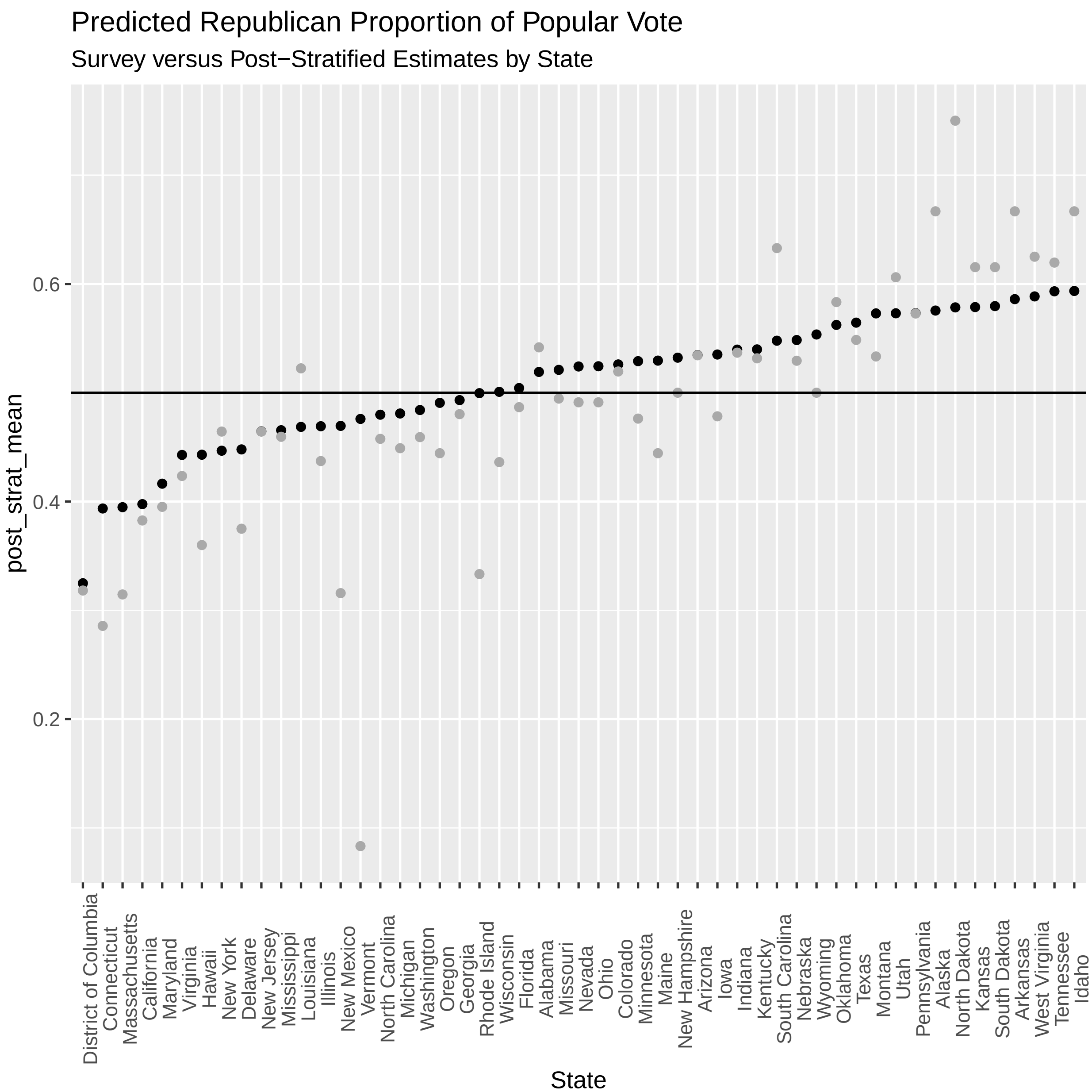

Figure 2: Survey versus poststrat by state.

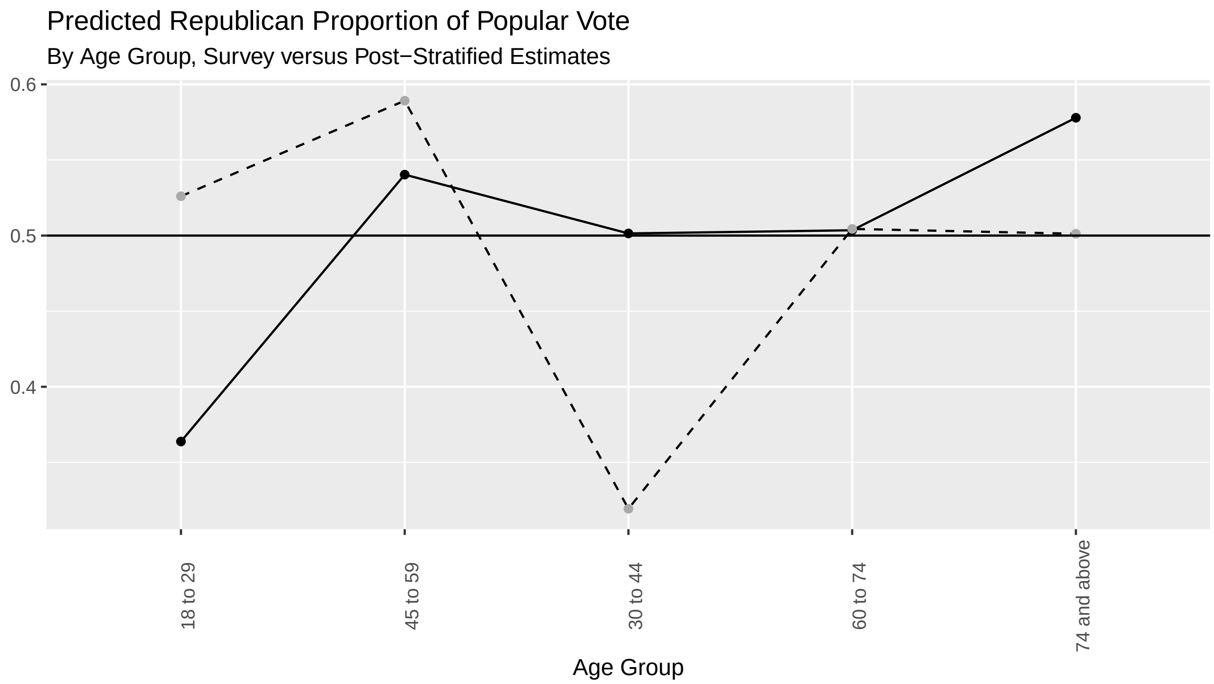

Figure 3: Survey versus poststrat by age

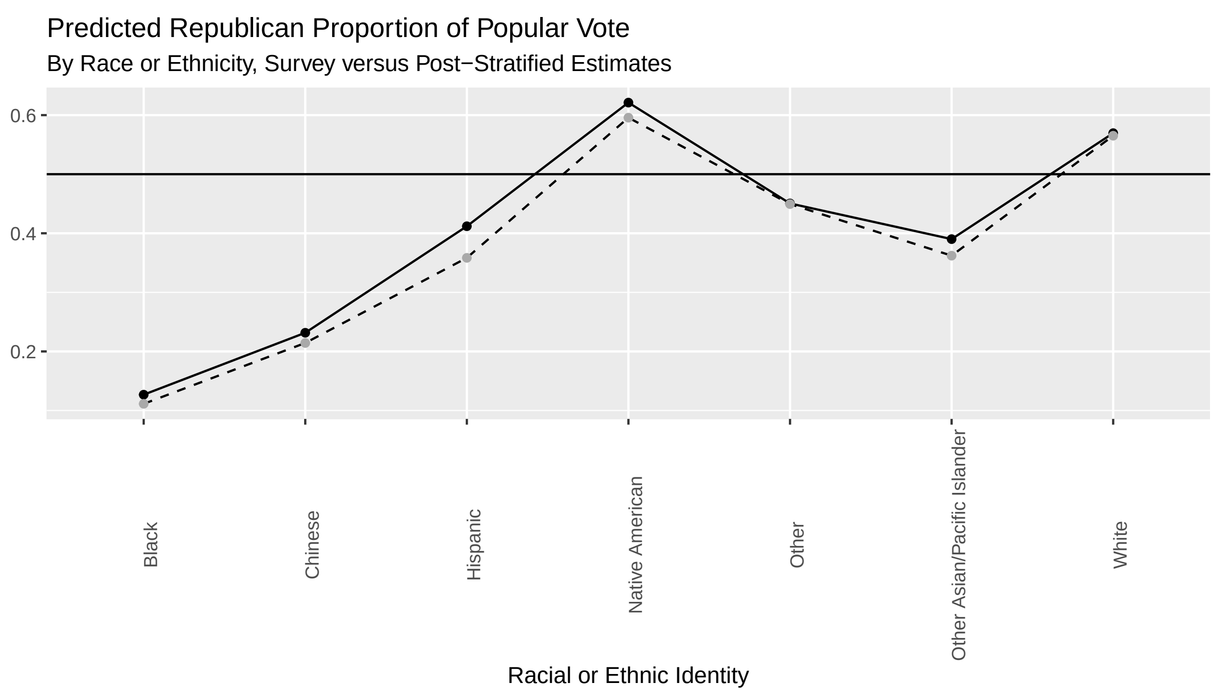

Figure 4: Predicted Republican vote by race

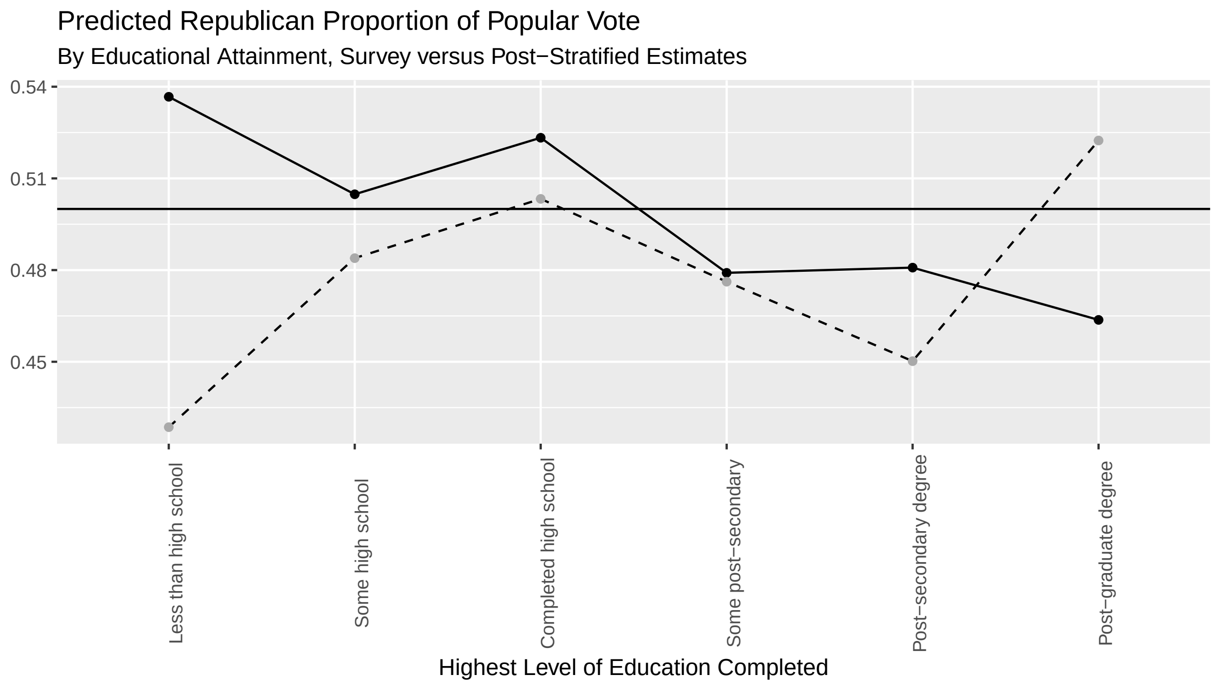

Figure 5: Education post-stratification estimates

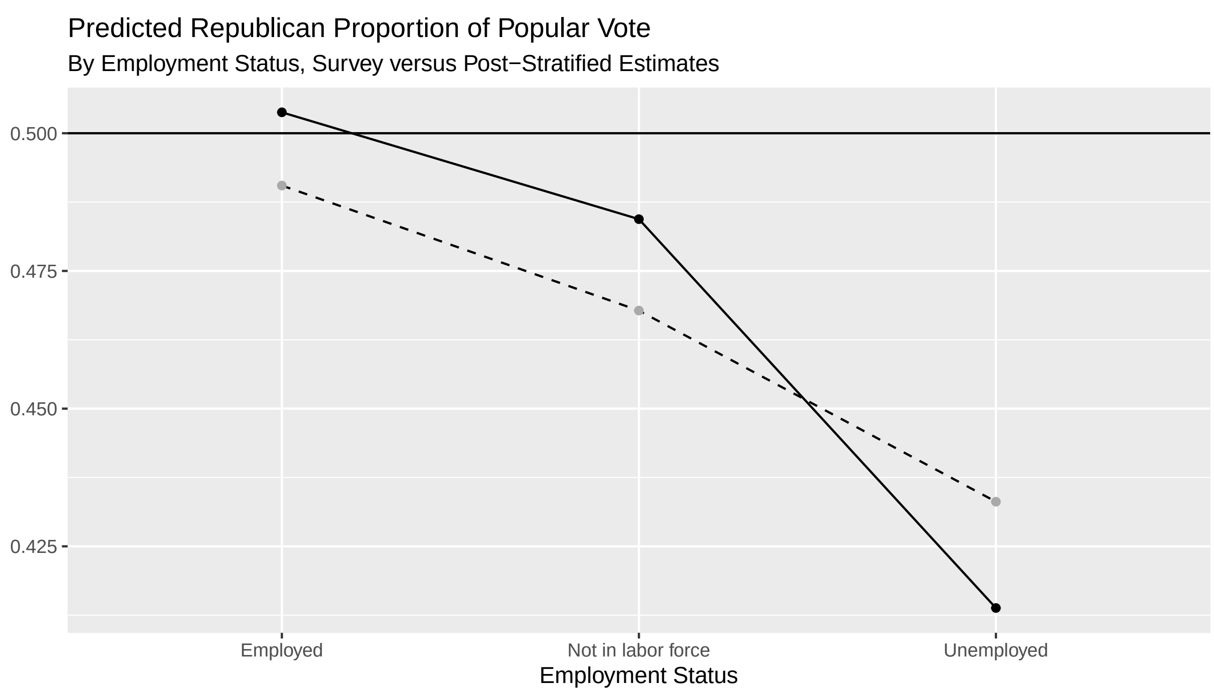

Figure 6: Employment post-stratification estimates

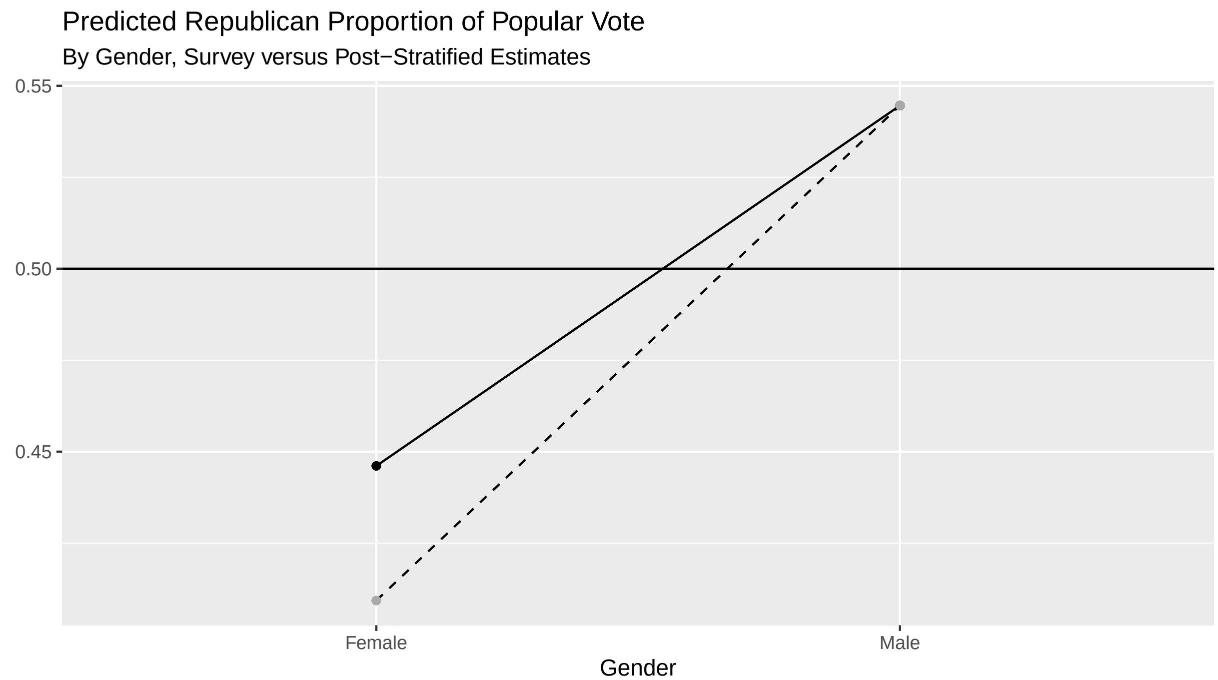

Figure 7: Gender post-stratification estimates

improving the predictive power of our model. For example, it is known that economic perceptions among voters may be important predictors for election outcomes (Duch and Stevenson, 2008) but we were not able to include such variables in our model. We now know that negative sentiment toward Muslim Americans was a strong and signficiant predictor of supporting Trump in the 2016 presidential election (Lajevardi and Abrajano, 2019). Some psychological patterns have also been observed among voters (Womick et al, 2019). Future work and post-stratification data will hopefully make available such important attitudinal issues that could help improve model specifications.

Another thing to note is that in this digital age, dramatic shifts in outcomes are perhaps possible in a very short period of time, such as the period of time between when we tested our model and the day of the election. In particular, we are worried about how search engine manipulation can affect the votes of undecided voters (Epstein and Robertson, 2015).

Researchers have shown that while intention is the single best predictor of behaviour–in our case, the intention to vote for Trump or Biden–it is also important to take into account other factors such as environmental constraints and the skills necessary to perform the behaviour (Fishbein and Ajzen, 2011). We have not been able to take into account the impact of COVID-19 on the ability of certain segments of the American population to participate in the vote. In particular, our predictions do not address the impact of postal ballots.

Future work can explore ways in which social media data–which have been shown to be useful predictors of election outcomes (e.g. Burnap et al., 2016; DiGrazia et al., 2013; Tumasjan et al., 2010)–can be combined with the MRP methodology to derive even more powerful predictive models. Perhaps new and creative sampling methods may need to be established to ensure statistically reliable sampling when working with social media data (Metaxas et al. 2011).

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