Biden More Favorable Among Female, Black, Asian, Hispanic, Middle Eastern, and Non-gun Owning Voters in the 2020 US Presidential Election*

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The outcome of the 2020 US Presidential Election served as a reflection of the beliefs and attitudes held by Americans. Using data obtained during the fall of 2020 from the Cooperative Election Study, we investigated if a person is likely to vote for Biden, based only on knowing their gender, race, and gun ownership status. The results of our analysis using a Bayesian logistic regression model show that female, Black, Asian, Hispanic, Middle Eastern, and non-gun owning individuals are more likely to support Biden. Our discovery highlights the importance of women's issues, racial justice, and gun policy on American voters.

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*Code and data are available at: https://github.com/atn-ly/political_support_in_the_us

1 Introduction

The United States (US) presidential election of 2020 resulted in President Joe Biden's victory, making him the 46th President of the US. The two top runners were Biden for the Democrats and former President Donald Trump for the Republicans. The presidential race between the two was of significant interest to statisticians and polling experts due to its potential impact on polling models and election forecasting. To provide some background, as former Vice President, President Biden had faced lots of scrutiny during his time in office. Likewise, former President Trump had controversial and career-damaging events. Before the 2020 elections, Trump was charged with misconduct while in office, but was acquitted by the Senate (USAGov 2012). Thus, both Biden and Trump have previously faced criticism from the electorate. An interesting question to consider is what characteristics did the voters have? Do they tell us a story on the type of people that voted for Biden and the type that voted for Trump? Answering these questions can help develop polling models and future election forecasting.

For our paper, we used a logistic regression model to estimate the likelihood of individuals voting for Biden or Trump, given certain characteristics. We used a binary outcome variable and three predictor variables. Our estimand is the probability that an individual voted for Biden or Trump based on three characteristics; their gender, race, and ownership of a gun. The reason for this choice will be further examined in Section 3. This approach to elections can bring insight to voter characteristics and the importance of survey data and knowing the electorate. We sought to produce results that could be used to predict voter behavior in the future.

Based on our model and analysis, our findings revealed that women were more likely to vote for Biden compared to Trump. This finding is consistent with broader trends in political behavior, as gender has previously shown to influence voting preferences. Biden's democratic policies were more convincing to women and will be discussed in Section 5. Another major finding was that Black, Asian, Hispanic, and Middle Eastern individuals were also more likely to vote for Biden. Biden has been widely known to run on a more progressive platform, giving importance on racial justice and addressing racial disparities. Our finding emphasizes that people from diverse and ethnic backgrounds are more inclined to vote for progressive representatives. Our final major finding was that non-gun owners were also more likely to vote for Biden. Gun owners often have strong opinions on gun control policies. Our finding shows that those who do not possess guns favored Biden's gun control and other firearm-related policies, as opposed to Trump's policies.

This paper was structured to communicate our model, results, and analysis to the reader in a strategic manner. Data for this analysis and the different applications used will be further introduced in Section 2. Section 3 provides the model set-up and the justification for the use of that model. Section 4 will show results and Section 5 is a discussion of the results including the paper's weaknesses and biases.

2 Data

2.1 Sources

The survey data for this paper is from the Harvard Dataverse Repository. The Cooperative Election Study is a sample survey in the Harvard Dataverse Repository that consists of pre-election and post-election questions with 61000 answers. They provide a guide and a dataset for numerous years. It is also open to the public. For this paper, we utilized the data from the 2020 Presidential Elections (Schaffner, Ansolabehere, and Luks 2021). The study was done to gain an understanding of "how Americans view Congress and hold their representatives accountable during elections, how they voted and their electoral experiences, and how their behaviour and experiences vary with political geography and social context" (Schaffner, Ansolabehere, and Luks 2021). The outcome of the 2020 election and every presidential election usually changes the direction of the country and demonstrates the perspectives of the majority of the electorate. Thus, this dataset was able to give us some clarity on perceptions of the electorate. There were similar datasets available, but we chose this one due to relevance to our research question. The questionnaire asked various questions on race, political party preference, voting preference, ownership of a gun and have numerous multiple choice answers available for each question. It was also easily accessible and we were able to adapt and adjust code from Telling Stories with Data (Alexander 2023) to suit our needs.

Our paper aims to address the following two questions using the data: (1) Does gender and race play a role in political preference? (2) Do those that own a gun favor one candidate over the other?

2.2 Methodology

The language and environment used for this analysis is `R` (R Core Team 2023), alongside the `tidyverse` (Wickham et al. 2019), `dataverse` (Kuriwaki, Beasley, and Leeper 2023), `arrow` (Richardson et al. 2024), `rstanarm` (Goodrich et al. 2022), `knitr` (Xie 2023), `here` (Müller 2020), `ggplot2` (Wickham 2016), `scales` (Wickham, Pedersen, and Seidel 2023), `modelsummary` (Arel-Bundock 2022), and `marginaleffects` (Arel-Bundock 2023) packages.

2.3 Variables

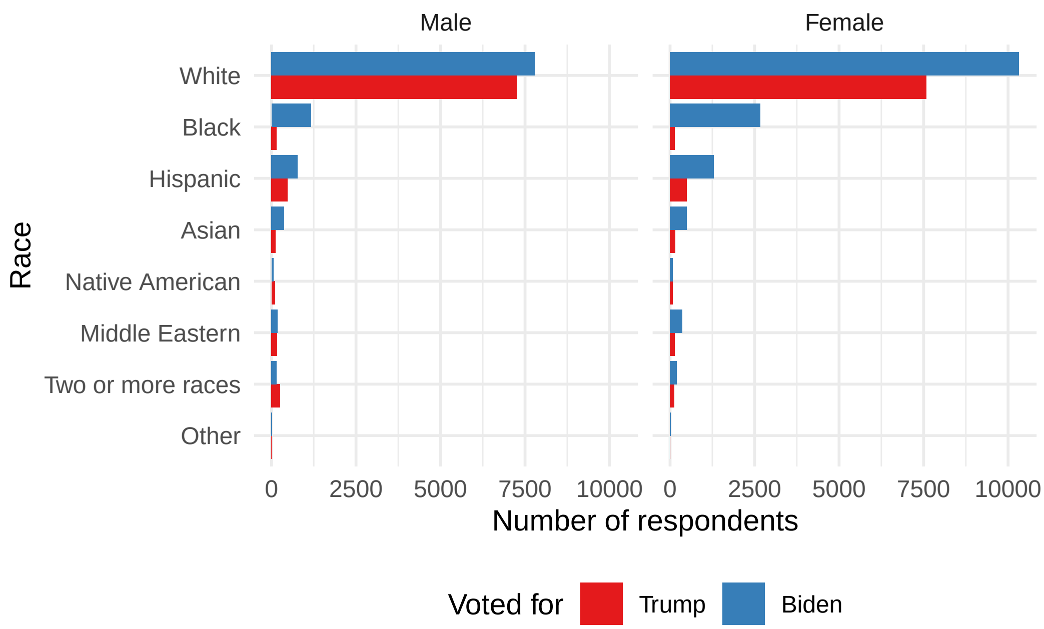


Figure 1: Support for Trump or Biden based on gender and race

From the dataset, we selected `gender`, `race`, and `gunown` from the pre-election questionnaire. In Figure 1, we can see support for the candidate based on gender and race. For gender, we were given two options in the study, male or female. For race, we considered eight options: White, Black, Hispanic, Asian, Native American, Middle Eastern, two or more races, and other. Note that only one selection was allowed in the original study for both gender and race.

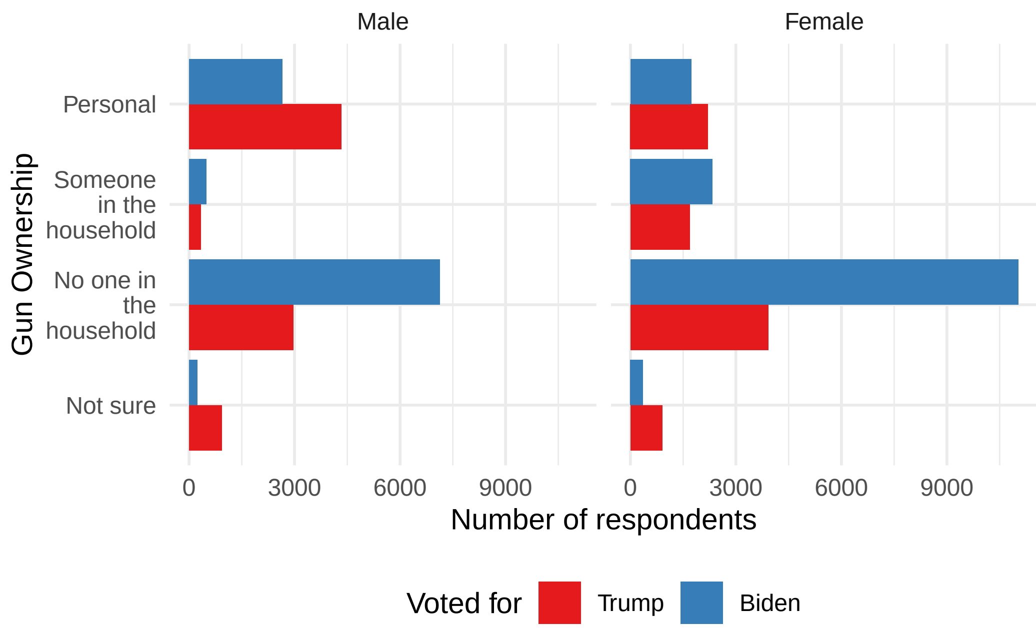


Figure 2: Support for Trump or Biden based on gender and gun ownership

Figure 2 illustrates the support for each candidate based on gun ownership status, with four options. Individuals who personally own a gun, who don't personally own one, but someone in their household owns a gun, no one in the household owns a gun, and not sure. We also selected a variable from the post-election questionnaire, the variable that recorded whether an individual voted for Biden or Trump in the 2020 Presidential election, `CC20_410`. This allowed us to establish a binary outcome variable for the probability of voting Biden or Trump in our model in Section 3.

Data was downloaded and cleaned to suit our needs and during the data cleaning process, we made sure to only include participants who were adults registered to vote. We also removed rows with NA values for `gunown`. This was due to the fact that we wanted to see individuals who answered all the questions for our variables of interest. We also limited the participants to those who explicitly stated they voted for Biden or Trump. Initially, other options were available to participants such as "I did not vote" and "not sure".

2.4 Measurement

We will now discuss how the variables, `gender`, `race`, and `gunown`, were measured and how they became an entry in our dataset. Each variable was associated with a related question, and the self-reported response of each individual from the online questionnaire was recorded in the dataset. Some notes on measurement error and missing data are required for each variable.

For the `gender` variable, individuals may choose to identify with diverse gender identities that are beyond the traditional categorization. The number of voters for genders other than male or female were not collected by CES, so we have missing data that we could not include in our analysis. From "Counting the Countless," this can be considered a result of what Keyes' refers to as the "administrative violence" that reinforces the gender binary (Keyes 2019).

For the `race` variable, participants were asked to select their ethnicity from one of the predetermined categories. Since this was an internet survey, this minimized the measurement error compared to other modes such as by a telephone interview conducted by a human. In the past, race has been of concern when an enumerator fills out the survey form on behalf of a respondent since it may limit the extent to which they describe their political belief (Alexander 2023).

For the `gunown` variable, participants were asked about their individual and household's gun ownership status. Since the survey conductors collect Personally Identifying Information (PII), such as name, email address, and postcode (YouGov 2023), respondents could be less likely to disclose their gun ownership status as it is a federal crime to possess illegal firearms.

3 Model

3.1 Model set-up

The goal of our modeling strategy is to forecast if a person is likely to vote for Biden, based only on knowing their gender, race, and gun ownership status.

The model that we are interested in is:

$$
\begin{aligned}
y_i|\pi_i &\sim \mathrm{Bern}(\pi_i) && (1)\\
\mathrm{logit}(\pi_i) &= \alpha + \beta \times \mathrm{gender}_i + \gamma \times \mathrm{education}_i + \delta \times \mathrm{gun}_i && (2)\\
\alpha &\sim \mathrm{Normal}(0, 2.5) && (3)\\
\beta &\sim \mathrm{Normal}(0, 2.5) && (4)\\
\gamma &\sim \mathrm{Normal}(0, 2.5) && (5)\\
\delta &\sim \mathrm{Normal}(0, 2.5) && (6)
\end{aligned}
$$

Where:

- y_i is the binary outcome variable, representing who respondent i voted for and equal to 1 if Biden and 0 if Trump,
- π_i is the probability that respondent i voted for Biden,
- $gender_i$ is a predictor variable, representing the gender of respondent i,

- $race_i$ is a predictor variable, representing the race of respondent i, and
- gun_i is a predictor variable, representing the gun ownership status of respondent i.

We used a logistic regression model in a Bayesian framework using the package `rstanarm` (Goodrich et al. 2022) in R (R Core Team 2023), which we will briefly describe here. Logistic regression is a type of generalized linear model. It is a tool for data exploration and used when we are interested in the relationship between a binary outcome variable and some predictor variables.

The foundation of logistic regression is the Bernoulli distribution and logit function. The Bernoulli distribution is a discrete probability distribution having two possible outcomes, "1" and "0", in which "1" occurs with probability p and "0" occurs with probability $1-p$. Logistic regression is still a linear model, because the predictor variables enter in a linear fashion (Alexander 2023). Hence, the logit function links the Bernoulli distribution to the machinery we use in linear models (Alexander 2023).

In our model, we also have the parameters α, β, γ, and δ in addition to the variables. The parameter α is the intercept and the parameters, β, γ, and δ, are the slope coefficients. We specify prior probability distributions for each of the parameters in our model. However, these are just the default priors that `rstanarm` (Goodrich et al. 2022) uses, which are Normal distributions with a mean and standard deviation of 0 and 2.5, respectively.

3.2 Model justification

Given that Biden and Trump are far apart on women's issues, racial justice, and gun policy, we chose "gender", "race", and "gunown" to be the predictor variables in our model. First, since we are interested in forecasting who a respondent is likely to vote for, we used "gender" instead of "gender_post" because it is representative of all adult Americans registered to vote rather than only adult Americans who voted. Second, we used "race" instead of variables by country or region to affirm that race is a social construct with no biological foundation. Third, we used "gunown" instead of variables about gun control because it captures broader opinions rather than specific policy proposals. After exploring the data in the previous section, we found differences in political preference based on these features and that it would be of interest to investigate further.

Logistic regression does not make the same assumptions as linear regression. First, linear regression assumes a continuous outcome variable that can take any number on the real line, whereas logistic regression assumes a binary outcome variable. Furthermore, linear regression requires that the outcome variable is a linear function of the predictor variables, while the outcome in logistic regression is part of the exponential family. However, logistic regression does assume that the relationship between the log-odds of the binary outcome and predictor variables is linear. Lastly, unlike in linear regression, logistic regression does not require the assumption of homoscedasticity of errors.

Alternative regression models were considered, but rejected because they were not appropriate for our outcome variable. Linear models assume a continuous outcome variable, and Poisson and Negative binomial models assume count outcome variables. Since our outcome variable is binary, we chose to use logistic regression.

To show that our model does a good job of fitting the data, we consider the posterior distribution and implement posterior predictive checks. Furthermore, we check if the Markov Chain Monte Carlo (MCMC) sampling algorithm that `rstanarm` uses to obtain samples from the posterior distributions of interest ran into any issues. Details and graphs can be found in Section B.

4 Results

We performed logistic regression analysis on 5000 observations; a subset of the total 43240 observations from our cleaned dataset. Since we are interested in which presidential candidate an individual voted for based on the categories explained earlier, our model made `genderMale`, `raceWhite`, `gun_ownershipPersonal` into reference groups for their respective categories.

Our results from the model given by Table 1 shows the coefficient of each indicator variable. This coefficient represents the log of the expected difference in support for Biden compared to Trump. When this value is negative, it shows a decrease in support for Biden, when this value is 0 it shows neither a decrease nor increase in support for Biden. When this value is positive, it shows an increase in support for Biden.

The intercept is -0.748 which means that the support for Biden decreases by about 0.784 units when all other variables are held constant. By holding all variables constant, we have an individual who is Male, White, and personally owns a gun.

4.1 Gender

We can see that for the variable `genderFemale`, we have a coefficient of 0.235 indicating an increase in support for Biden over the reference group being `genderMale`, while keeping the other variables constant.

4.2 Race

We can see that Black individuals show a much stronger support for Biden as the coefficient for `raceBlack` is 2.464. Asian, Hispanic, and Middle Eastern individuals all show an increase in support for Biden with coefficients of 0.790, 0.548, and 0.288 respectively. Native Americans and Other show a decrease in support for Biden with a coefficient of -0.536 and -0.333 respectively while individuals of two or more races show neither an increase nor decrease in support for Biden with a coefficient of -0.008.

Table 1: Explanatory models of political preferences based on gender, race, and gun ownership (n = 5000)

	Support Biden
(Intercept)	−0.748
	(0.067)
genderFemale	0.235
	(0.067)
raceBlack	2.464
	(0.184)
raceHispanic	0.548
	(0.122)
raceAsian	0.790
	(0.203)
raceNative American	−0.536
	(0.403)
raceMiddle Eastern	0.288
	(0.218)
raceTwo or more races	−0.008
	(0.252)
raceOther	−0.333
	(0.905)
gun_ownershipSomeone in the household	0.870
	(0.112)
gun_ownershipNo one in the household	1.332
	(0.072)
gun_ownershipNot sure	−0.815
	(0.157)
Num.Obs.	5000
R2	0.175
Log.Lik.	−2898.226
ELPD	−2910.6
ELPD s.e.	30.1
LOOIC	5821.1
LOOIC s.e.	60.2
WAIC	5821.0
RMSE	0.45

4.3 Gun Ownership

For gun ownership, we can see that if an individual does not personally own a gun but someone in their household does, the coefficient is 0.870 which shows an increase in support for Biden. If nobody in an individual's household owns a gun, the coefficient is 1.332 showing a strong support for Biden. When an individual does not own a gun and is not sure if anyone in their household owns a gun, the coefficient is -0.815 showing a decrease in support for Biden.

Table 2: Probability that an individual supports Biden given their demographic

rowid	estimate	conf.low	conf.high	voted_for	gender	race	gun_ownership
1	0.7511584	0.6631003	0.8273150	Biden	Female	Middle Eastern	No one in the household
2	0.7564311	0.7087319	0.7988593	Trump	Male	Hispanic	No one in the household
3	0.3741561	0.3412633	0.4101036	Biden	Female	White	Personal
4	0.6941046	0.6708337	0.7161842	Trump	Female	White	No one in the household
5	0.5875198	0.5431017	0.6310208	Trump	Female	White	Someone in the household
6	0.7971713	0.7557982	0.8334727	Biden	Female	Hispanic	No one in the household

From the model, we used `predictions()` from `marginaleffects` (Arel-Bundock 2023) to obtain the implied probability that an individual supports Biden. A sample of the result is given in Table 2 where each individual is given an `estimate` value which is the estimated probability that the individual supports Biden.

Using the results in Table 2, we plotted three graphs using `ggplot2` (Wickham 2016) which shows the estimated probability that an individual supports Biden given gender, race, and gun ownership with the colour of the point indicating their true support. Figure 3 shows the estimated probability that an individual supports Biden given gender. To support the accuracy of our model, blue dots should be higher up on the graph while red dots should be lower down indicating that our predicted probability matches with the actual result. We can see in Figure 3 that this trend holds true.

Figure 4 shows the estimated probability that an individual supports Biden given race. There appears to be red dots near the top for White, Native American, Middle Eastern, and Two or more races which indicates possible inaccuracy in our model. However, Black, Hispanic and Asian appears to follow the expected distribution of the dots.

Figure 5 shows the estimated probability that an individual supports Biden given their gun ownership status. We can see that the "Personal" and "Not sure" categories show a lower

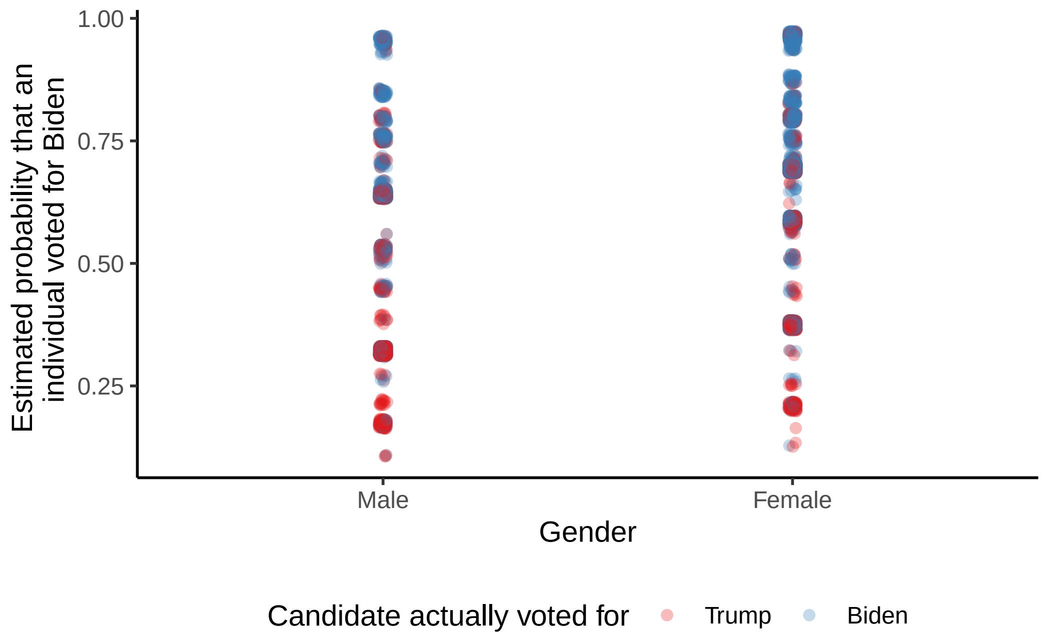


Figure 3: Predicted support of Biden given gender vs. actual support

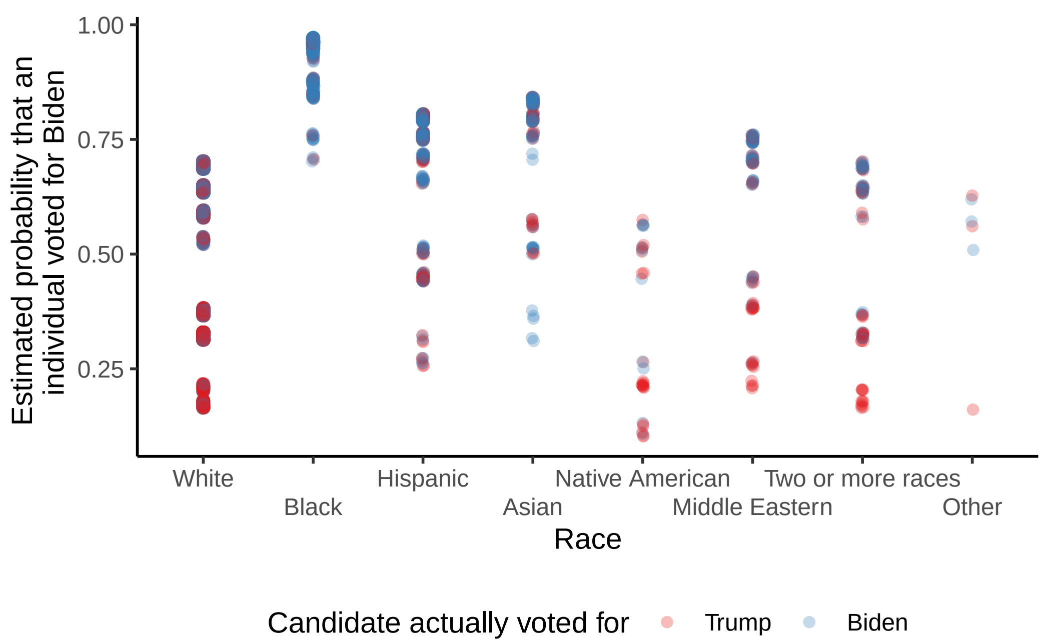


Figure 4: Predicted support of Biden given race vs. actual support

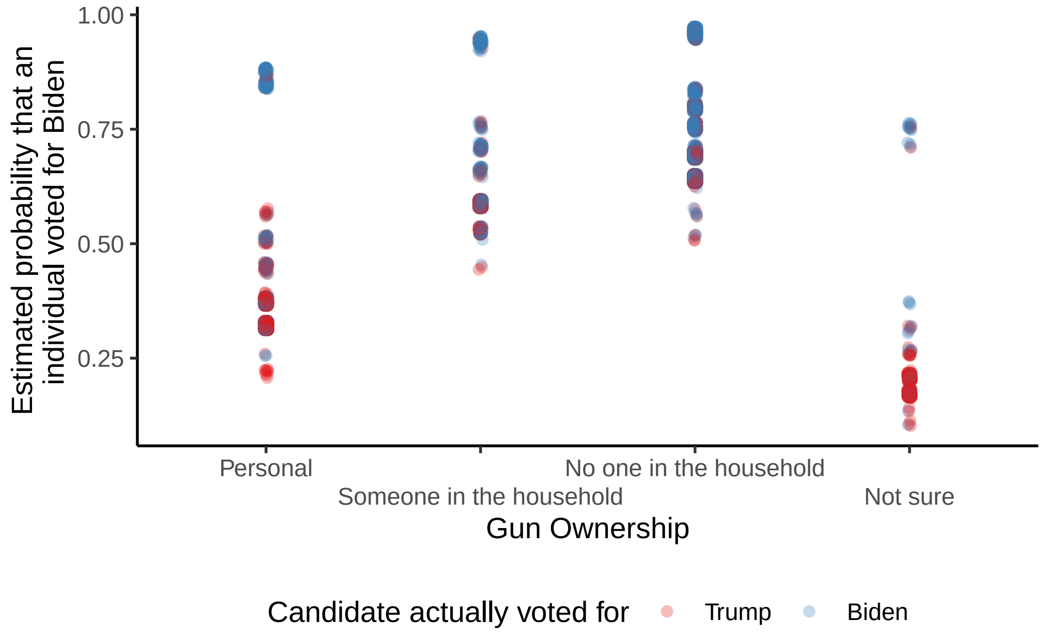


Figure 5: Predicted support of Biden given gun ownership vs. actual support

support of Biden, while the "No One in the household" and the "Someone in the household" categories show a higher trend of support for Biden. There appears to be an expected cluster of blue dots higher up and red dots lower down, which supports the accuracy of our model.

5 Discussion

5.1 Findings

In this paper, data from the 2020 Cooperative Election Study (CES) (Schaffner, Ansolabehere, and Luks 2021) of US political opinion was downloaded and cleaned as discussed in Section 2. Then, we used a Bayesian logistic regression model as seen in Section 3 to forecast if a person is likely to support Biden, based only on knowing their gender, race, and gun ownership status. Following the outcomes of our analysis in Section 4, we summarize our three major results here:

1. Women are more likely to vote for Biden,
2. Black, Asian, Hispanic, and Middle Eastern individuals are more likely to vote for Biden, and
3. Non-gun owners are more likely to vote for Biden.

We will now justify and detail the implications of our results by providing the political, historical, cultural, and social context that shaped our story of American political preference in the 2020 US presidential election.

5.2 Women are more likely to vote for Biden

In Section 4, we found that women have a coefficient of 0.235 and higher estimated probabilities that our model implies of supporting Biden. This means that by just knowing that an individual is female, we can forecast that they are more likely to vote for Biden. Our results imply that Biden's policies on women's issues are more favorable than Trump's. This confirms what we expected as Biden and Trump held opposing stances on various important women's issues during the 2020 election including women's reproductive rights, women's health, and violence against women.

Abortion is a key issue and a deal-breaker for many voters during an election. During Biden's 2020 campaign, he vowed to protect a women's right to choose and keep access to abortion legal (BBC 2020). In particular, Biden promised to protect and codify *Roe v Wade*, a landmark Supreme Court ruling from 1973, which decriminalized abortion nationwide (BBC 2020). In contrast, Trump pushed for the overturning of *Roe* and appointed conservative anti-abortion judges during his presidency (BBC 2020).

Moreover, women's health is another important issue that voters consider when deciding which candidate to support. During the 2020 election, Biden supported women's access to coverage and care (Long 2020). For example, Biden campaigned to protect the 2010 *Affordable Care Act*, which provides affordable healthcare to millions of women in the US and restricts discriminatory insurance policies (Long 2020). This contrasts with Trump's stance on women's health in which he supported to overturn the entire *ACA* with no plan to replace it (Long 2020).

Furthermore, the issue of sexual violence has been of increasing importance as 1 in 3 women and 1 in 4 men in the US report experiencing sexual violence in their lifetimes (Long 2020). During his time as a senator, Biden passed the 1994 *Violence Against Women's Act* which helped establish many violence prevention efforts including rape crisis centers, shelters, and other support services (Long 2020). During his 2020 campaign, Biden supported reauthorizing and expanding this law, whereas Trump allowed the law to expire in 2018 during his presidency and stated no position on his campaign website (Long 2020).

We learn that Biden and Trump have stark differences on women's issues and that the outcome of the 2020 election would have major consequences for women. As seen in our findings, women are more likely to vote for Biden, reflecting their support for policies that protect their rights.

5.3 Black, Asian, Hispanic, and Middle Eastern individuals are more likely to vote for Biden

In Section 4, we found that Black, Asian, Hispanic, and Middle Eastern individuals have coefficients of 2.464, 0.790, 0.548, and 0.288 respectively and higher estimated probabilities that our model implies of supporting Biden. This means that by just knowing that an individual is Black, Asian, Hispanic, or Middle Eastern, we can forecast that they are more likely to vote for Biden. Our results imply that Biden's policies on racial justice are more favorable than Trump's within marginalized communities. This aligns with our expectations as Biden and Trump held opposing stances on various important racial issues during the 2020 election including Black Lives Matter, minority-owned small businesses, and housing and education.

In 2020, the police killings of George Floyd in May and Breonna Taylor in March sparked the largest racial justice protests across the US (Gomez 2020). As a result, racial equality was at the center of many voter's minds during the 2020 election. Biden's legacy of Black support was demonstrated by his choice of Kamala Harris as his running mate, as she is the first woman, the first Black American, and the first South Asian American to hold this position (Gomez 2020). In contrast, Trump called Black Lives Matter "a symbol of hate" and encouraged police violence against protestors (Gomez 2020).

Additionally, Biden and Trump had different strategies to address racial disparities within the US including wealth, opportunity, and job gaps (Moore 2020). In 2020, Biden pledged to support minority-owned small businesses with a 26-page plan that includes investing $30 billion toward a Small Business Opportunity Fund, $50 billion in venture capital for Black and brown entrepreneurs, and $100 billion toward low-interest loans for new entrepreneurs (Moore 2020). This is in stark contrast to Trump, who had no broad policy plan to address racial economic inequality (Moore 2020).

Housing and education is another important issue in combating racial inequality in the US. Biden proposed to boost homeownership among minority communities by creating a housing-plan that includes constructing 1.5 million homes and public housing units and ending discriminatory housing policies (Moore 2020). On education reform, Biden proposed to make public universities and private historically Black colleges and universities tuition-free for families with incomes under $125,000 (Moore 2020). Again, Trump had no plans in place to address these issues (Moore 2020).

We learn that Biden and Trump are far apart on racial justice and that the 2020 election would shape the lives of many non-white people for years to come. As seen in our findings, Black, Asian, Hispanic, and Middle Eastern individuals are more likely to vote for Biden, reflecting their support for anti-racist policies that promote equality.

5.4 Non-gun owners are more likely to vote for Biden

In Section 4, we found that non-gun owning individuals with non-gun owning households have a coefficient of 1.332 and higher estimated probabilities that our model implies of supporting Biden. This means that by just knowing that an individual and whose household does not own a gun, we can forecast that they are more likely to vote for Biden. Our results imply that Biden's gun policies were more favorable than Trump's for non-gun owners. This confirms what we expected as Biden and Trump held opposing stances on various important policies including gun control, universal background checks, and assault weapons bans.

With the rise in mass shootings and gun-related deaths across the country, safe gun policies are as important as ever (Hill 2020). Under the Trump administration, the US saw record-breaking tragedies in the 2017 Las Vegas Strip shooting, 2017 Sutherland Springs church shooting, 2018 Parkland high school shooting, and 2019 El Paso shooting (Hill 2020). During his presidency, Trump supported Second Amendment rights and pushed for greater freedom for gun-owners (Staff 2020). He loosened gun regulations on firearms exports and reversed a law that allowed people deemed mentally unfit to purchase guns (Staff 2020). In contrast, during Biden's 2020 campaign, he included plans to require universal background checks for all gun sales and bans on semiautomatic rifles and magazines that contained more than 10 bullets (Hill 2020).

We learn that Biden and Trump have opposite approaches to gun policies and that the outcome of the 2020 election would decide the safety of millions of Americans. As seen in our findings, non-gun owners are more likely to vote for Biden, reflecting their support for policies that prevent gun violence.

5.5 Weaknesses and next steps

Weaknesses arise in the data and model that was used. Although the sampling methodology detailed in Schaffner, Ansolabehere, and Luks (2021) is an accepted approach that balances sampling concerns and cost, there are still limitations with large survey data that must be addressed. First, while the survey was not directly conducted by the government, it was conducted by YouGov, an international online research data and analytics technology group, that was funded by the government (YouGov 2023). This affects our findings since their clients could be Democrats or Republicans that have their own partisan goals in mind (YouGov 2023). Historically, there have been cases of data manipulation to suit a government's narrative in the past (Alexander 2023). Moreover, there will always be missing data no matter how good the data acquisition process is (Alexander 2023). CES respondents are people who have made an account on yougov.com or recruited live from online advertisements, and the 2020 CES survey was conducted over the internet (Schaffner, Ansolabehere, and Luks 2021). However, 1 in 5 US households are not connected to the internet at home (Cao 2022). This affects our findings since the sample is representative of Americans with internet access rather than of all national adults as Schaffner, Ansolabehere, and Luks (2021) claims.

In future work, we could include additional predictor variables to get a more complete picture of the opinions and traits of American voters. For example, the results using family income, educational level, and state of residence as variables, along with their implications, could be of interest. Moreover, we could include the other two presidential candidates of the Libertarian and Green Party in future studies, which would require a different model. Lastly, another aspect to consider could be investigating the post-election questionnaire data. We could build the model again using the post-election data and compare the results with our findings from the pre-election data.

Appendix

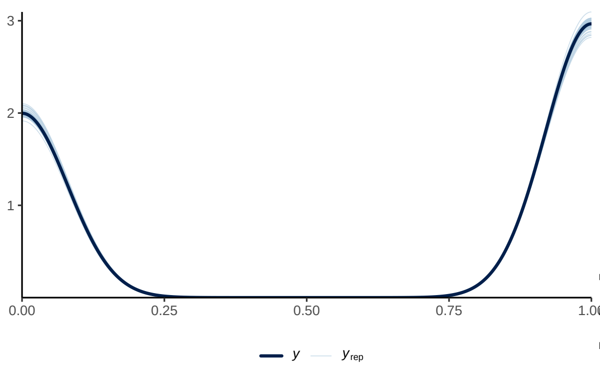
A Additional data details

B Model details

B.1 Posterior predictive check

In Figure 6a we implement a posterior predictive check. It shows a very close match between the actual outcome variable with simulations from the posterior distribution. This suggests that our model does a good job of fitting the data.

In Figure 6b we compare the posterior with the prior. It shows that estimates changed minimally once the data was taken into account. This suggests that we specified good priors.



(a) Posterior prediction check

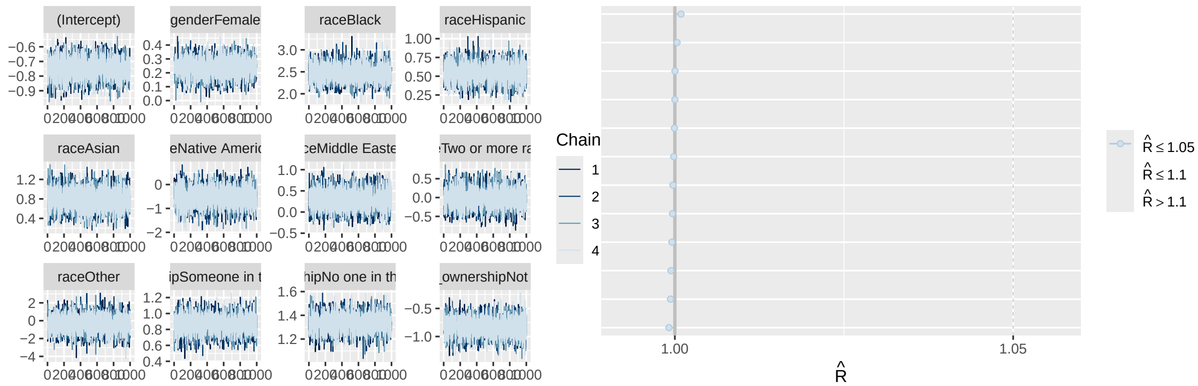
(b) Comparing the posterior with the prior

Figure 6: Examining how the model fits, and is affected by, the data

B.2 Diagnostics

Figure 7a is a trace plot. It shows that there are no horizontal lines that appear to bounce around and have a nice overlap between the chains. This does not suggest anything out of the ordinary.

Figure 7b is a Rhat plot. It shows that everything is close to 1 and no more than 1.1. This does not suggest any problems.



(a) Trace plot

(b) Rhat plot

Figure 7: Checking the convergence of the MCMC algorithm

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