My title*

My subtitle if needed

First author

Another author

March 8, 2024

First sentence. Second sentence. Third sentence. Fourth sentence.

1 Introduction

You can and should cross-reference sections and sub-sections. We use R Core Team (2023) and Wickham et al. (2019).

The remainder of this paper is structured as follows. Section 2....

2 Data

Some of our data is of penguins (?@fig-bills), from Horst, Hill, and Gorman (2020).

^{*}Code and data are available at: https://github.com/hannahyu07/US-Election

```
# change column type to factor
ces2020 <-
  ces2020 |>
  mutate(
    voted_for = as_factor(voted_for),
    race = factor(
      race,
      levels = c(
        "White",
        "Black",
        "Hispanic",
        "Asian",
        "Native American",
        "Middle Eastern",
        "Two or more races",
        "Other"
      )
    ),
    region = factor(
      region,
      levels = c(
        "Northeast",
        "Midwest",
        "South",
        "West"
      )
    ),
    employ = factor(
      employ,
      levels = c(
        "Full-time",
        "Part-time",
        "Temporarily laid off",
        "Unemployed",
        "Retired",
        "Permanently disabled",
        "Homemaker",
        "Student",
        "Other"
      )
    )
```

) |>
select(voted_for, race, region, employ)

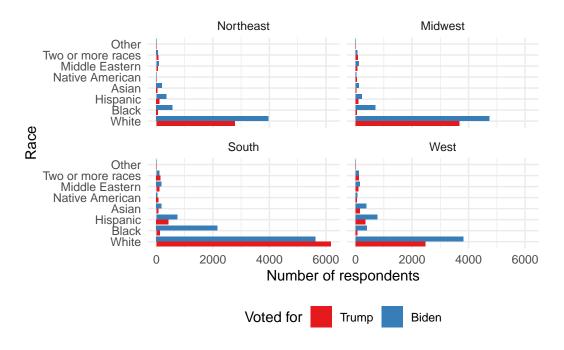


Figure 1: The distribution of presidential preferences, by region and race

Talk more about it.

And also planes (?@fig-planes). (You can change the height and width, but don't worry about doing that until you have finished every other aspect of the paper - Quarto will try to make it look nice and the defaults usually work well once you have enough text.)

Talk way more about it.

3 Model

The goal of our modelling strategy is twofold. Firstly,...

Here we briefly describe the Bayesian analysis model used to investigate... Background details and diagnostics are included in

Appendix B.

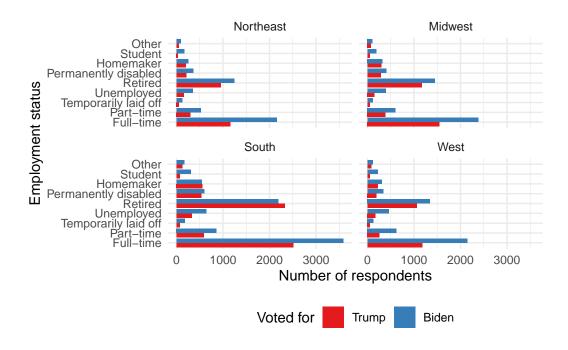


Figure 2: The distribution of presidential preferences, by region and employment status

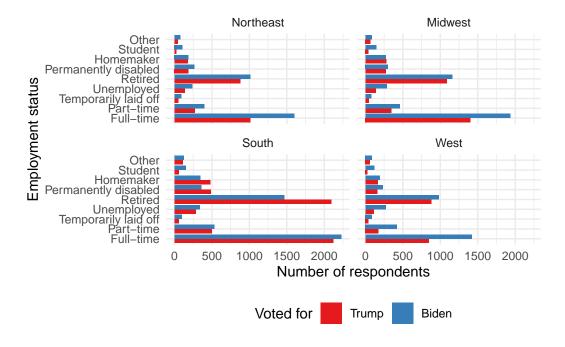


Figure 3: The distribution of presidential preferences, by region and employment status, only white people

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$y_i | \pi_i \sim \text{Bern}(\pi_i)$$
 (1)

$$\operatorname{logit}(\pi_i) = \alpha + \beta_1 \times \operatorname{race}_i + \beta_2 \times \operatorname{region}_i + \beta_3 \times \operatorname{employ}_i \tag{2}$$

$$\alpha \sim \text{Normal}(0, 2.5)$$
 (3)

$$\beta_1 \sim \text{Normal}(0, 2.5)$$
 (4)

$$\beta_2 \sim \text{Normal}(0, 2.5)$$
 (5)

We run the model in R (R Core Team 2023) using the rstanarm package of Goodrich et al. (2022). We use the default priors from rstanarm.

3.1.1 Model justification

We expect a positive relationship between individuals of Black, Asian, and Hispanic ethnicities and support for Biden. This expectation arises from Trump's history of spreading polarizing language and anti-immigrant sentiments, as well as his controversial plans such as building a border wall. These groups are more likely to align with Biden's policies, which prioritize inclusivity and diversity. White individuals with traditional family values and conservative leanings tend to support Trump. They are drawn to his emphasis on preserving traditional values and promises to uphold conservative principles, especially regarding immigration, law and order, and gun rights.

Conversely, we anticipate a negative relationship between voters in the South and Midwest regions and support for Biden. These regions have a stronger conservative presence and a history of supporting Republican candidates like Trump. States such as Texas and Florida, which are known Republican strongholds, are located in the South. Therefore, individuals in these regions may be less inclined to support Biden's progressive agenda.

Regarding employment status, we expect students, unemployed individuals, and those temporarily laid off to be more inclined to support Biden. Students are often exposed to diverse perspectives and progressive ideas in educational settings, making them more likely to endorse Biden's platform. Unemployed and laid-off individuals may favor Biden due to the Democratic Party's advocacy for social welfare programs and support for workers' rights.

The voting behavior of employed individuals is harder to distinguish. Some working individuals support Trump due to their opposition to higher taxes and prefer his promises of tax cuts and economic deregulation. Conversely, others lean towards Biden because they believe tax increases should primarily target the wealthy and not burden the middle class. Additionally,

educated and liberal-leaning working professionals may prioritize issues such as healthcare, climate change, and social justice, aligning them with Biden's platform.

4 Results

Our results are summarized in ?@tbl-modelresults.

```
# Print the updated model summary with modified variable names
  print(
    modelsummary(
      list("Support Biden" = political preferences1),
      statistic = "mad",
      coef_map = list(
        Intercept = "Intercept",
        raceBlack = "Black",
        raceHispanic = "Hispanic",
        raceMiddle_Eastern = "Middle Eastern",
        raceNative_American = "Native American",
        raceOther = "Other race",
        `raceTwo or more races` = "Two or more races",
        raceWhite = "White",
        regionNortheast = "Northeast",
        regionSouth = "South",
        regionWest = "West",
        employHomemaker = "Homemaker",
        employOther = "Other employment",
        employPart_time = "Part-time",
        employPermanently_disabled = "Permanently disabled",
        employRetired = "Retired",
        employStudent = "Student",
        `employTemporarily laid off` = "Temporarily laid off",
        employUnemployed = "Unemployed"
      )
    )
  )
\begin{table}
\centering
\begin{tabular}[t]{lc}
\toprule
 & Support Biden\\
```

Table 1: Explanatory models Political Preferences (n = 1000)

	Support Biden
(Intercept)	0.806
	(0.438)
raceBlack	2.549
	(0.683)
raceHispanic	$0.039^{'}$
-	(0.503)
raceMiddle Eastern	-0.162
	(0.649)
raceNative American	-2.791
	(1.288)
raceOther	37.999
	(33.885)
raceTwo or more races	-1.900
	(0.769)
raceWhite	-0.650
	(0.436)
${\it regionNortheast}$	0.436
	(0.217)
$\operatorname{regionSouth}$	-0.161
	(0.186)
regionWest	0.137
	(0.206)
${ m employ Homemaker}$	-0.187
	(0.297)
employOther	0.298
	(0.557)
employPart-time	0.433
	(0.270)
employPermanently disabled	-0.273
	(0.295)
employRetired	-0.200
	(0.168)
${ m employStudent}$	0.831
	(0.501)
employTemporarily laid off	0.699
	(0.553)
${\it employUnemployed}$	0.416
	(0.331)
Num.Obs.	1000
R2	0.118
Log.Lik.	-606.898
ELPD	-627.2
ELPD s.e. 7	11.8
LOOIC	1254.4
LOOIC s.e.	23.6
WAIC	1253.7
RMSE	0.46

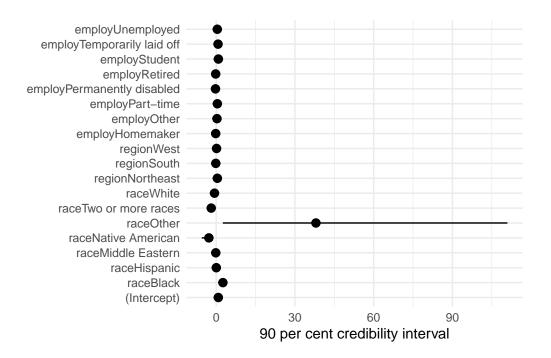
```
\midrule
Black & \num{2.549}\\
 & (\num{0.683})\\
Hispanic & \num{0.039}\\
 & (\num{0.503})\\
Other race & \num{37.999}\\
 & (\num{33.885})\\
Two or more races & \sum_{-1.900}
 & (\num{0.769})\\
White & \sum_{-0.650}
 & (\num{0.436})\\
Northeast & \sum{0.436}
 & (\num{0.217})\\
South & \num{-0.161}\\
 & (\num{0.186})\\
West & \num{0.137}\\
 & (\num{0.206})\\
Homemaker & \num{-0.187}\\
 & (\num{0.297})\\
Other employment & \num{0.298}\\
 & (\num{0.557})\\
Retired & \num{-0.200}\\
 & (\num{0.168})\\
Student & \num{0.831}\\
 & (\num{0.501})\\
Temporarily laid off & \num{0.699}\\
 & (\num{0.553})\\
Unemployed & \sum{0.416}
 & (\num{0.331})\\
\midrule
Num.Obs. & \num{1000}\\
R2 & \num{0.118}\\
Log.Lik. & \num{-606.898}\\
ELPD & \num{-627.2}\\
ELPD s.e. & \sum{11.8}
LOOIC & \num{1254.4}\\
LOOIC s.e. & \sum{23.6}
WAIC & \num{1253.7}\\
RMSE & \num{0.46}\\
\bottomrule
\end{tabular}
```

\end{table}

```
# Extract posterior samples
# posterior_samples <- as.matrix(political_preferences)
#
# Calculate credible intervals (e.g., 95%)
# credible_intervals <- apply(posterior_samples, 2, function(x) quantile(x, c(0.025, 0.975))
# # Extract coefficient names
# coefficient_names <- colnames(posterior_samples)
# # Create a data frame with coefficient names, coefficient estimates, and credible interval table_data <- data.frame(
# Posterior_Mean = colMeans(posterior_samples),
# Credible_Interval_Lower = credible_intervals[1, ],
# Credible_Interval_Upper = credible_intervals[2, ]
# )
# # Print the table
# print(table_data)</pre>
```

Due to the fact that the credibility interval for race Other is particularly large, we cannot observe the trend of the 90% credibility intervals of other variables. That's why we created a second plot with the x axis limited from -10 to 10.

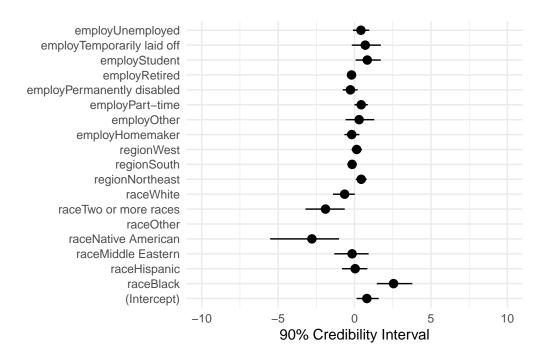
```
modelplot(political_preferences1, conf_level = 0.9) +
labs(x = "90 per cent credibility interval")
```



```
# Create the model plot
model_plot <- modelplot(political_preferences1, conf_level = 0.9)

# Modify the x-axis limits
model_plot + xlim(-10, 10) + # Adjust the limits as needed
labs(x = "90% Credibility Interval")</pre>
```

Warning: Removed 1 rows containing missing values (`geom_pointrange()`).



5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

In **?@fig-ppcheckandposteriorvsprior-1** we implement a posterior predictive check. This shows...

In **?@fig-ppcheckandposteriorvsprior-2** we compare the posterior with the prior. This shows...

Examining how the model fits, and is affected by, the data

Figure 4: ?(caption)

B.2 Diagnostics

?@fig-stanareyouokay-1 is a trace plot. It shows... This suggests...

?@fig-stanareyouokay-2 is a Rhat plot. It shows... This suggests...

Checking the convergence of the MCMC algorithm

Figure 5: ?(caption)

References

- Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. "Rstanarm: Bayesian Applied Regression Modeling via Stan." https://mc-stan.org/rstanarm/.
- Horst, Allison Marie, Alison Presmanes Hill, and Kristen B Gorman. 2020. Palmerpenguins: Palmer Archipelago (Antarctica) Penguin Data. https://doi.org/10.5281/zenodo. 3960218.
- R Core Team. 2023. R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.
- Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.