Modeling U.S. Presidential Election Outcomes Using Aggregated Poll Data[*]

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This study leverages a poll-of-polls approach to forecast support for candidates in the 2024 U.S. Presidential Election. By aggregating multiple polls and weighting by sample size, we minimize biases inherent in individual polls and generate a more robust prediction model. Our analysis uses a generalized linear model to project each candidate's support level on election day, revealing Michelle Obama, Kamala Harris, and Bernie Sanders as the top contenders. These findings highlight the power of aggregated polling in providing a clearer picture of candidate standings, with implications for campaign strategy and public understanding of election dynamics.

1 Introduction

Introduction

The 2024 U.S. presidential election has drawn significant public interest, with voters keenly following candidates' standings across various polls. Given the influence of aggregated polling data in shaping public opinion, forecasting the election outcome has become a valuable exercise for researchers, media, and the public alike. This paper leverages a "poll-of-polls" methodology to provide a data-driven forecast of the election results, aggregating multiple polls to reduce individual poll biases and improve predictive accuracy. By analyzing this aggregated data, we aim to identify trends, provide insights into each candidate's standing, and ultimately forecast the most likely winner.

Our primary goal is to estimate the level of support for each presidential candidate as of election day. Using weekly aggregated polling data weighted by sample size, we build a generalized linear model (GLM) to predict candidate support on a future date. This model incorporates both the candidate and time (weekly) as predictors, providing a robust estimation of expected

[*] Code and data are available at: https://github.com/RohanAlexander/starter_folder.

support levels based on trends observed over the election cycle. By focusing on the poll-of-polls approach, we seek to enhance accuracy over individual polls by averaging out sampling errors and biases.

The analysis reveals a competitive race among several candidates, with Michelle Obama, Kamala Harris, and Bernie Sanders emerging as leading contenders based on predicted support levels. Our model suggests that Michelle Obama is likely to receive the highest support on election day, positioning her as the probable winner if these trends persist. The results highlight the importance of aggregating polling data, as individual poll variations are smoothed out, allowing for a clearer picture of each candidate's standing in the national context.

This forecasting model provides more than just an election prediction; it offers a method for systematically understanding polling data and its implications. In an era where polling accuracy is increasingly scrutinized, this approach adds value by minimizing biases associated with individual polls. Accurate forecasting models can inform campaign strategies, guide media narratives, and help the public interpret the shifting dynamics of candidate support. Moreover, this study underscores the potential of statistical modeling in addressing real-world questions and adds to the literature on poll aggregation and political forecasting.

The remainder of this paper is structured as follows. Section 2 presents the data preparation steps, including cleaning and aggregation procedures. Section 3 details the modeling approach, explaining the rationale for using a generalized linear model and the interpretation of model coefficients. Section 4 discusses the results, including the forecasted support for each candidate and the projected election outcome. Section 5 offers a deep-dive analysis of one selected pollster's methodology, examining sampling methods, response rates, and questionnaire design. Section 6 proposes an idealized survey methodology for future election forecasting, addressing sampling, recruitment, and data validation with a hypothetical $100,000 budget. Finally, Section 7 concludes with a summary of findings and recommendations for future work.

2 Data

2.1 Overview

We use the statistical programming language R (R Core Team 2023) to conduct our analysis, leveraging its robust libraries for data manipulation, visualization, and statistical modeling. Our data source is primarily polling data, capturing various metrics from multiple pollsters over time. Following Alexander (2023), this data allows us to explore trends and make inferences about public support for different candidates.

The dataset used in this analysis provides polling results for the 2024 US presidential election, collected from various sources and aggregated into a single dataset. Each entry in the dataset represents an individual poll, including information on sample size, candidate support percentages, pollster methodology, and other variables.

2.2 Measurement

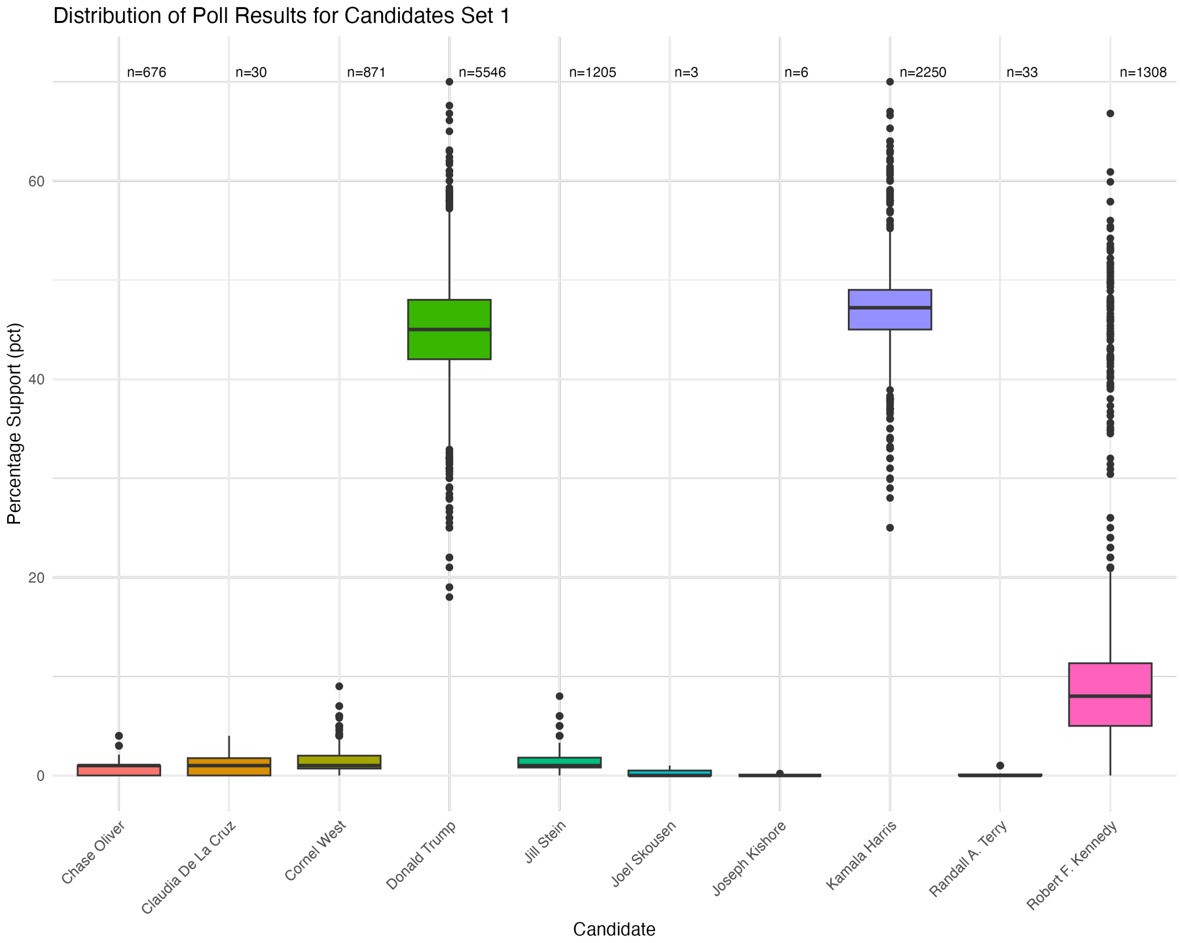
To ensure data accuracy, each polling metric (such as sample size and percentage support) was standardized across pollsters. This involved harmonizing the definitions of key variables and ensuring that all metrics were consistent. This section provides an understanding of how raw polling results translate into usable data for forecasting the election.

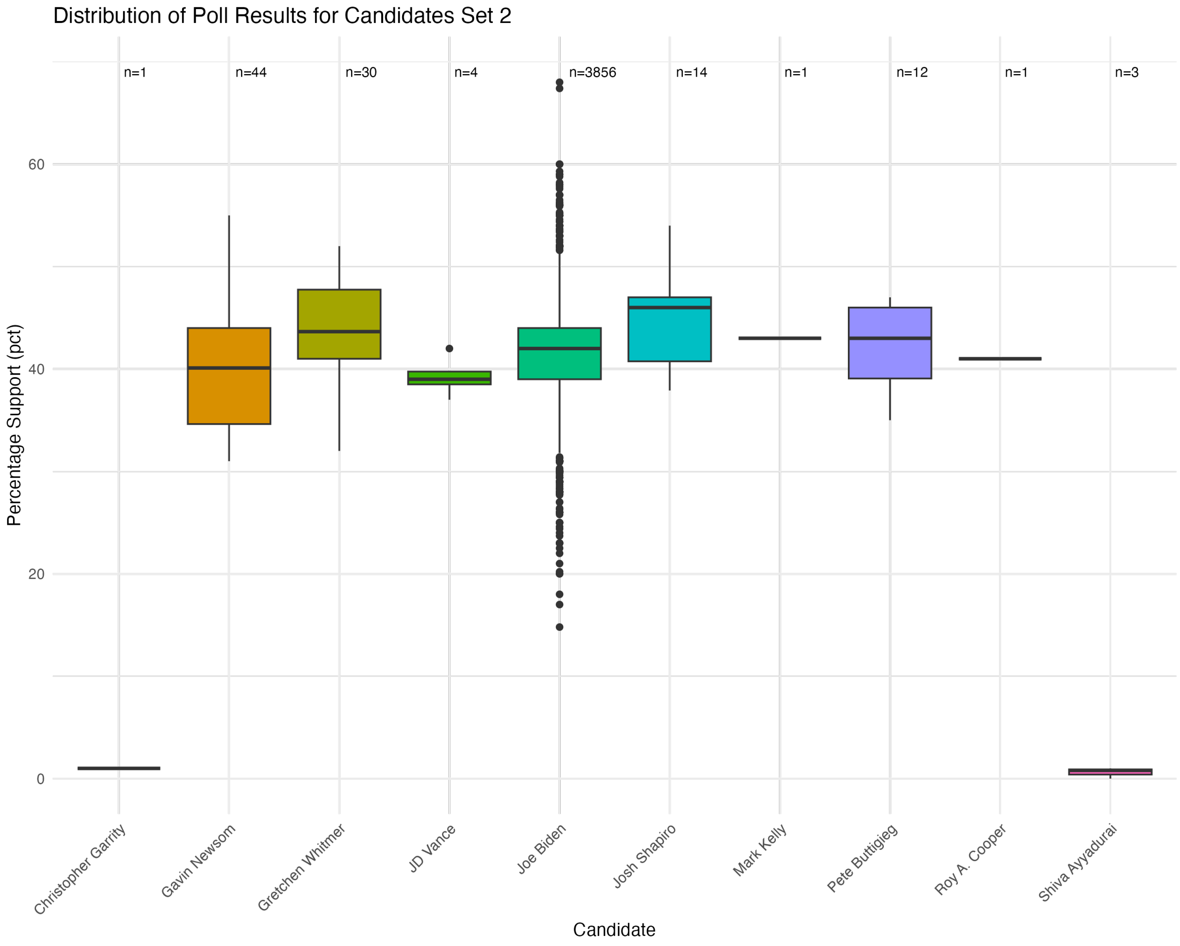
2.3 Outcome Variables

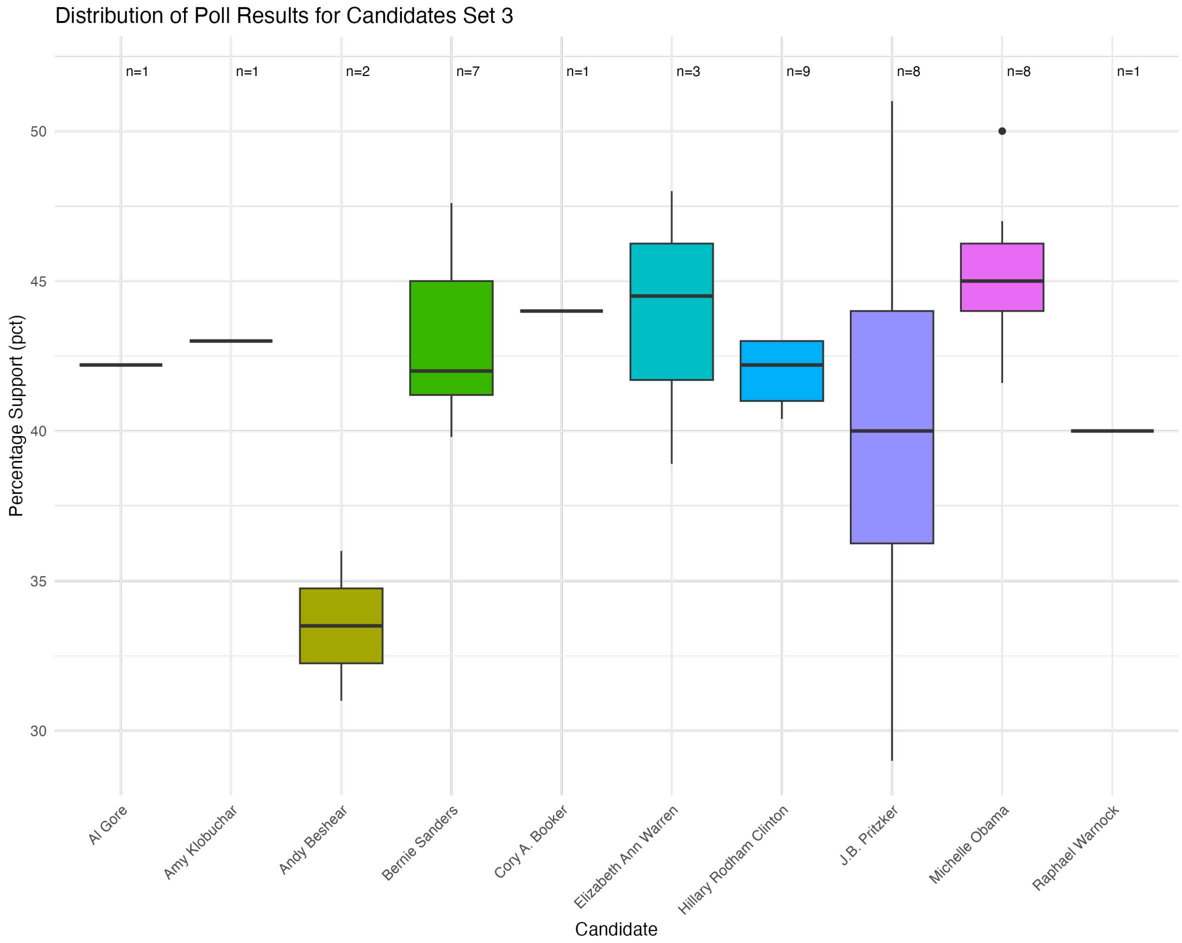
This analysis focuses on polling data that measures support for various candidates. Each outcome variable represents the weighted support percentage for a candidate based on polls conducted at different times. Outcome variables were derived by calculating weighted averages, considering sample size as a weight.

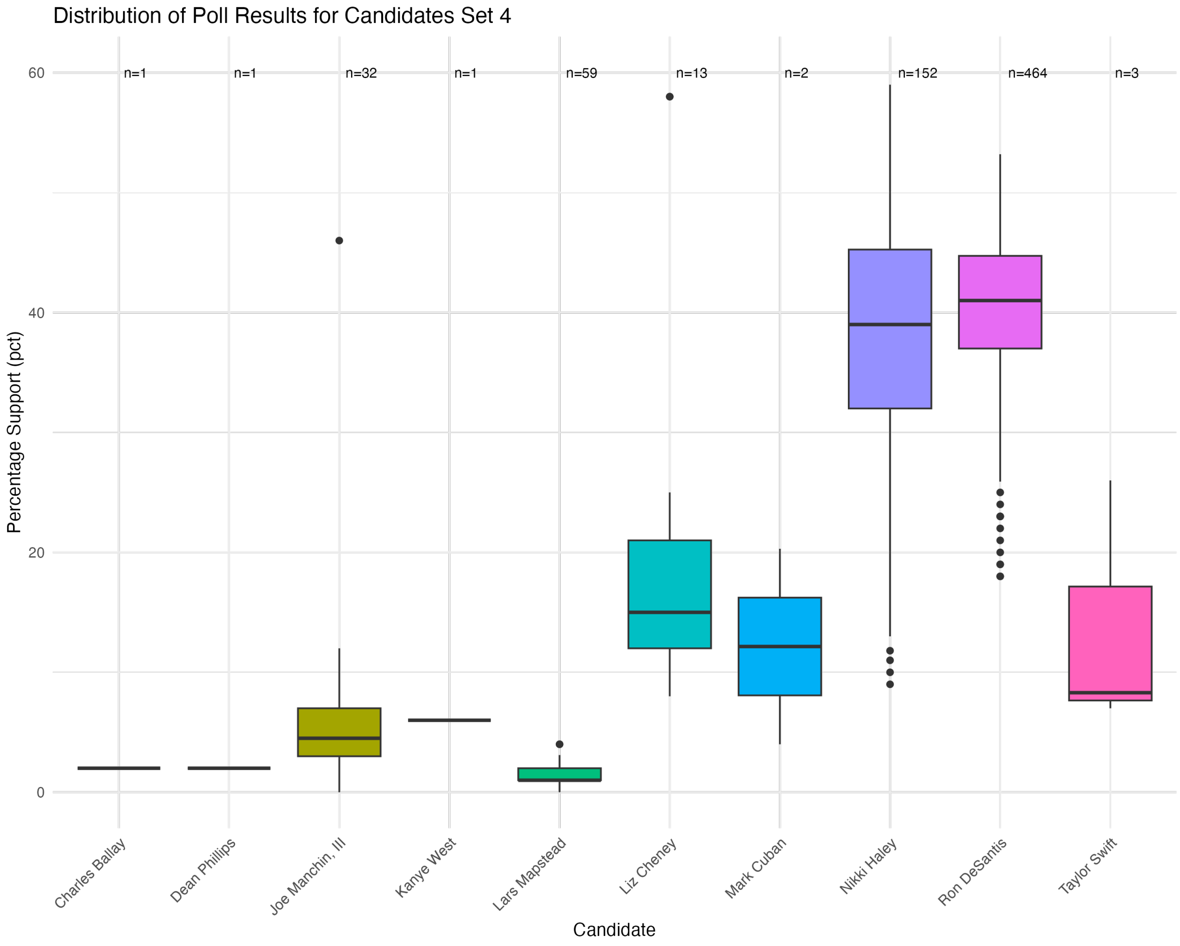
2.3.1 Candidate Support Distributions

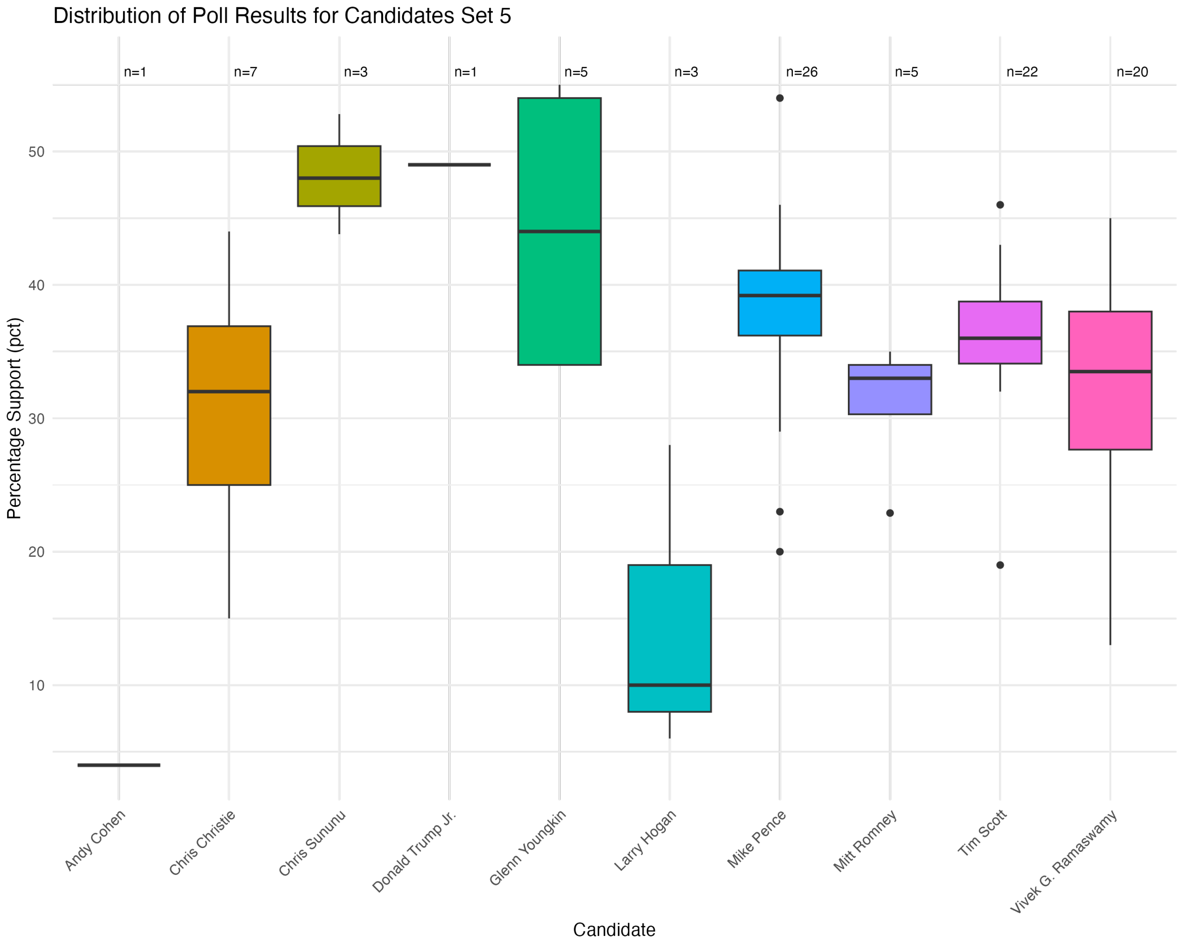
Each set of candidates has a corresponding boxplot showing the distribution of their support percentages across polls, with the sample size for each candidate indicated by an `n` label.

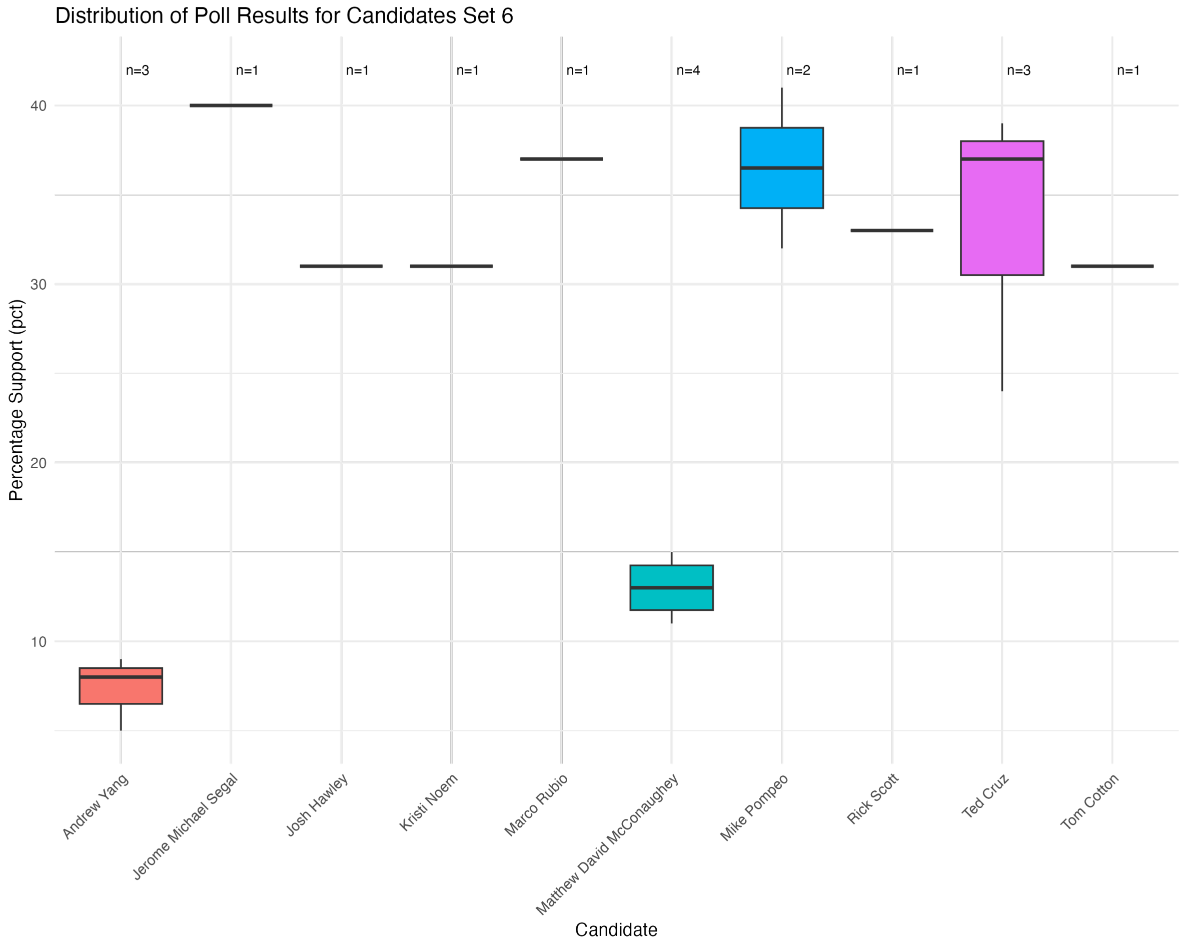

Distribution of Poll Results for Candidates Set 1
n=676
n=30
n=871
n=5546
n=1205
n=3
n=6
n=2250
n=33
n=1308
Percentage Support (pct)
60
40
20
0
Chase Oliver
Claudia De La Cruz
Cornel West
Donald Trump
Jill Stein
Joel Skousen
Joseph Kishore
Kamala Harris
Randall A. Terry
Robert F. Kennedy
Candidate

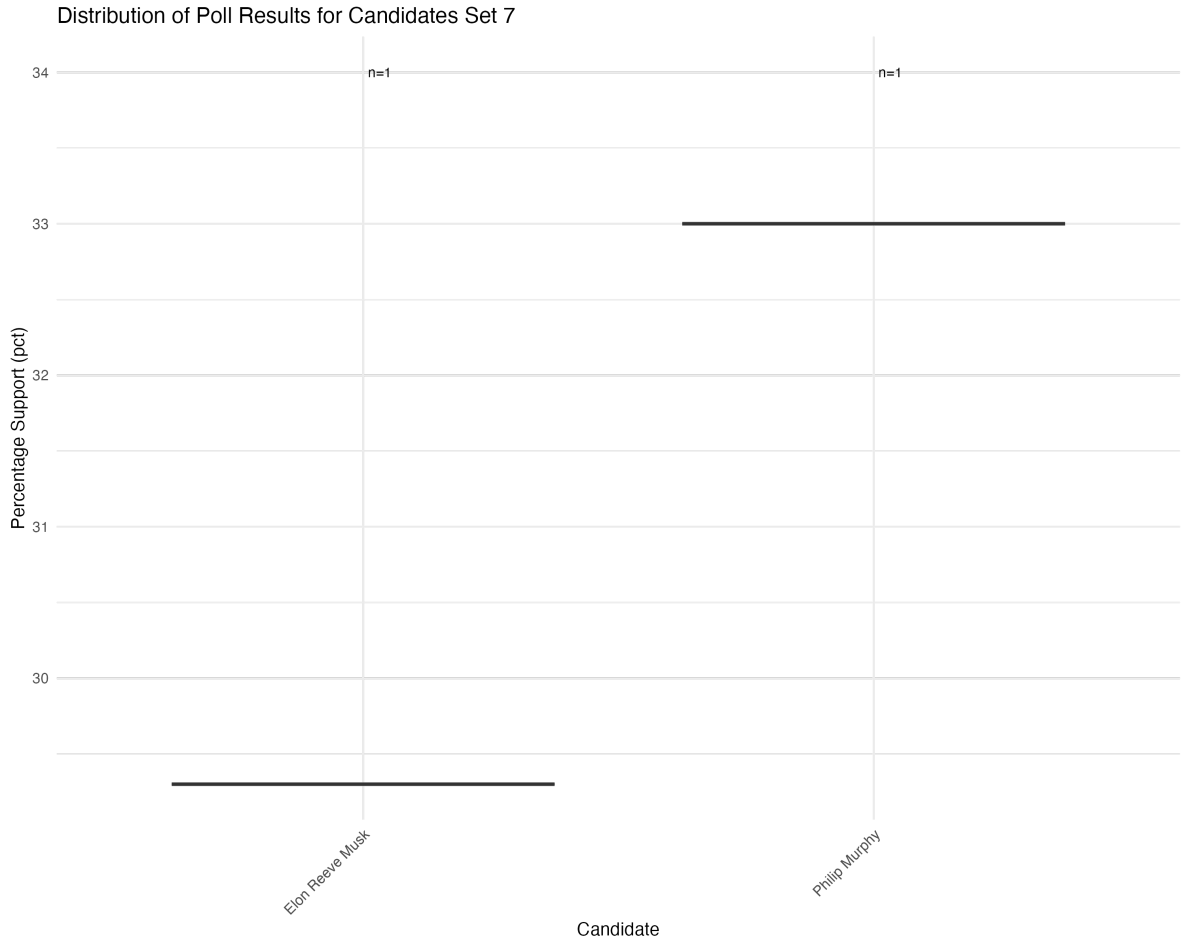

Distribution of Poll Results for Candidates Set 2
n=1
n=44
n=30
n=4
n=3856
n=14
n=1
n=12
n=1
n=3
Percentage Support (pct)
60
40
20
0
Christopher Garrity
Gavin Newsom
Gretchen Whitmer
JD Vance
Joe Biden
Josh Shapiro
Mark Kelly
Pete Buttigieg
Roy A. Cooper
Shiva Ayyadurai
Candidate


Distribution of Poll Results for Candidates Set 3
n=1
n=1
n=2
n=7
n=1
n=3
n=9
n=8
n=8
n=1
50
45
40
35
30
Percentage Support (pct)
Al Gore
Amy Klobuchar
Andy Beshear
Bernie Sanders
Cory A. Booker
Elizabeth Ann Warren
Hillary Rodham Clinton
J.B. Pritzker
Michelle Obama
Raphael Warnock
Candidate


Distribution of Poll Results for Candidates Set 4
Percentage Support (pct)
0
20
40
60
n=1
n=1
n=32
n=1
n=59
n=13
n=2
n=152
n=464
n=3
Charles Ballay
Dean Phillips
Joe Manchin, III
Kanye West
Lars Mapstead
Liz Cheney
Mark Cuban
Nikki Haley
Ron DeSantis
Taylor Swift
Candidate


Distribution of Poll Results for Candidates Set 5
n=1
n=7
n=3
n=1
n=5
n=3
n=26
n=5
n=22
n=20
Percentage Support (pct)
50
40
30
20
10
Andy Cohen
Chris Christie
Chris Sununu
Donald Trump Jr.
Glenn Youngkin
Larry Hogan
Mike Pence
Mitt Romney
Tim Scott
Vivek G. Ramaswamy
Candidate


Distribution of Poll Results for Candidates Set 6
Percentage Support (pct)
10
20
30
40
n=3
n=1
n=1
n=1
n=1
n=4
n=2
n=1
n=3
n=1
Andrew Yang
Jerome Michael Segal
Josh Hawley
Kristi Noem
Marco Rubio
Matthew David McConaughey
Mike Pompeo
Rick Scott
Ted Cruz
Tom Cotton
Candidate



Some candidates show a wide range of support percentages across polls, while others have a more concentrated range. For example, Donald Trump and Joe Biden typically show wider interquartile ranges (IQRs) compared to others, indicating a greater variability in their polling results. This could be due to regional differences or variations in specific poll methodologies. In contrast, candidates like Michelle Obama or Nikki Haley have narrower boxes, suggesting more consistent levels of support across the polls included. Median Support Levels:

The median line within each box gives an indication of the central tendency of support for each candidate. For instance, Donald Trump often has a median close to 40-45%, while Joe Biden also has a similar range, reflecting their position as leading candidates. Candidates with lower medians, such as Chris Christie or Mike Pence, have median support values significantly lower, indicating that they are generally less favored across the polls. Outliers:

Some candidates exhibit outliers, which could represent unusually high or low support in certain polls. These outliers might result from specific regional polls where a candidate has localized support or from methodological differences between polls. Outliers are particularly noticeable for candidates like Donald Trump and Joe Biden, indicating that their support can significantly vary depending on the poll or region. Sample Size (n):

The "n" labels beside each candidate indicate the number of polls that included that candidate. Higher values of "n" suggest that these candidates are being more widely polled, which often correlates with higher public interest or relevance. Candidates with low "n" values may have limited data, which could affect the reliability of their displayed support range. For instance, if a candidate is only included in a few polls, their polling box may not accurately reflect broader public sentiment.

2.3.2 Support Trend by Sample Size

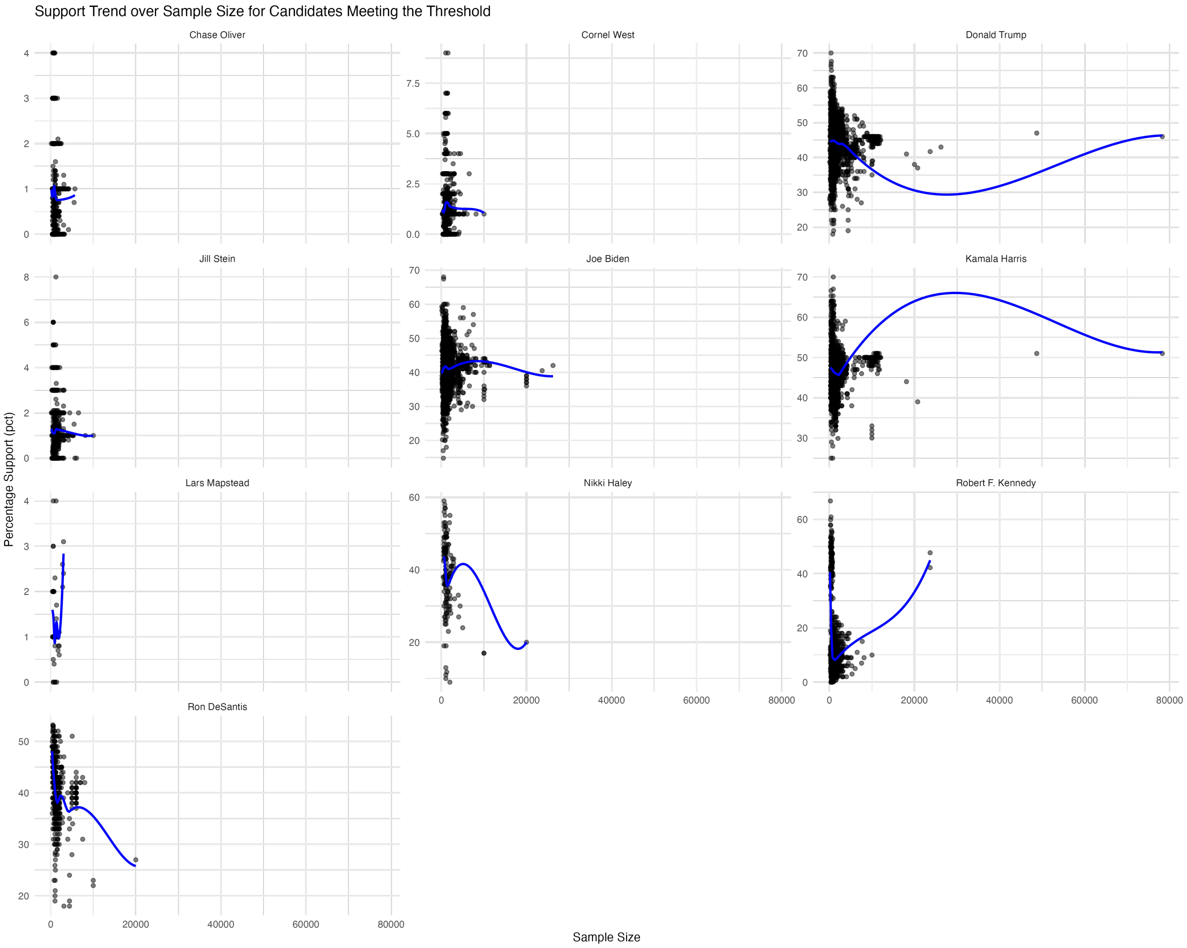


Figure 1: Sample Size and Candidate Support

This figure displays the relationship between sample size and candidate support levels across different polls.

Donald Trump and Joe Biden exhibit more stable trends with larger sample sizes, although both show some variations. Kamala Harris displays an upward trend in her early data with small sample sizes, but this trend stabilizes as the sample size increases. Ron DeSantis and Robert F. Kennedy show interesting trends, with DeSantis having a downward slope in support as sample size increases, while Kennedy shows a slight upward trend. Candidates with Low Support Across All Polls:

Candidates like Chase Oliver, Cornel West, and Jill Stein consistently show very low support percentages, with their LOESS curves staying close to the bottom of the y-axis. This suggests that these candidates have minimal support regardless of poll sample size. Variability in Support Based on Sample Size:

For some candidates, support seems sensitive to sample size changes, indicating potential variability in their appeal depending on polling conditions. Nikki Haley, for example, shows a decline in support as sample sizes grow. Lars Mapstead and Kamala Harris exhibit trends that fluctuate with sample size, which may reflect niche support that's more visible in smaller or region-specific polls.

```
# A tibble: 10 x 2
   pollster                                        count
   <chr>                                           <int>
 1 Morning Consult                                  2417
 2 Redfield & Wilton Strategies                     1146
 3 Emerson                                          1033
 4 YouGov                                            891
 5 Siena/NYT                                         719
 6 Beacon/Shaw                                       427
 7 Echelon Insights                                  418
 8 Ipsos                                             404
 9 McLaughlin                                        343
10 Florida Atlantic University/Mainstreet Research   306
```

3 Model

The goal of our modeling strategy is twofold. First, to forecast support for each candidate based on polling data, adjusted for sample size and week. Second, to identify candidates who show significant changes in support over time, which could be important predictors in the context of the upcoming election.

3.1 Model Set-Up

In our model, we define `weighted_support` as the aggregate weekly support for each candidate, weighted by the sample size of each poll. The support levels are then modeled as a function of `candidate_name` and `week` using a Generalized Linear Model (GLM) with a Gaussian family.

The GLM formula used is: $weighted_support = candidate_name + week$ This model setup allows us to observe general support trends across all candidates, as well as weekly variations in individual support levels. The model was run using the R programming language (R Core Team 2023).

3.1.1 Model Justification

Given the historical consistency in candidate polling, we anticipate that `candidate_name` will have a significant effect on support levels, with time trends captured through the `week` variable. This approach provides a baseline for understanding candidate standings and forecasting future support, with an assumption of gradual change in support levels over time.

```
Call:
glm(formula = weighted_support ~ candidate_name + week, family = gaussian(),
    data = weekly_support)

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                              3.931e+01  4.138e+00   9.500  < 2e-16
candidate_nameAndy Beshear              -8.888e+00  5.475e+00  -1.623  0.10483
candidate_nameBernie Sanders             2.436e+00  4.742e+00   0.514  0.60757
candidate_nameChase Oliver              -4.145e+01  3.915e+00 -10.585  < 2e-16
candidate_nameChris Christie            -7.999e+00  4.471e+00  -1.789  0.07391
candidate_nameChris Sununu               1.934e+00  5.478e+00   0.353  0.72418
candidate_nameClaudia De La Cruz        -4.134e+01  4.107e+00 -10.066  < 2e-16
candidate_nameCornel West               -4.078e+01  3.892e+00 -10.480  < 2e-16
candidate_nameDonald Trump               9.006e-01  3.883e+00   0.232  0.81663
candidate_nameElizabeth Ann Warren       1.613e+00  4.470e+00   0.361  0.71835
candidate_nameGavin Newsom               1.087e+00  4.007e+00   0.271  0.78626
candidate_nameGlenn Youngkin             2.139e+00  4.742e+00   0.451  0.65210
candidate_nameGretchen Whitmer           7.201e-01  4.044e+00   0.178  0.85870
candidate_nameHillary Rodham Clinton     2.578e-01  4.471e+00   0.058  0.95403
candidate_nameJ.B. Pritzker             -1.220e+00  4.329e+00  -0.282  0.77812
candidate_nameJerome Michael Segal      -2.417e+00  5.476e+00  -0.441  0.65905
candidate_nameJill Stein                -4.077e+01  3.892e+00 -10.475  < 2e-16
```

```
candidate_nameJoe Biden                  2.166e-01 3.883e+00   0.056  0.95553
candidate_nameJoe Manchin, III          -3.676e+01 4.060e+00  -9.052  < 2e-16
candidate_nameJoel Skousen              -4.240e+01 5.476e+00  -7.743 2.47e-14
candidate_nameJoseph Kishore            -4.241e+01 4.743e+00  -8.941  < 2e-16
candidate_nameJosh Hawley               -1.148e+01 5.477e+00  -2.095  0.03640
candidate_nameJosh Shapiro              -7.845e-01 4.328e+00  -0.181  0.85622
candidate_nameKamala Harris              2.437e+00 3.898e+00   0.625  0.53195
candidate_nameKanye West                -3.594e+01 5.477e+00  -6.563 8.63e-11
candidate_nameKristi Noem               -1.148e+01 5.477e+00  -2.095  0.03640
candidate_nameLarry Hogan               -1.448e+01 5.477e+00  -2.643  0.00835
candidate_nameLars Mapstead             -4.056e+01 4.109e+00  -9.871  < 2e-16
candidate_nameLiz Cheney                -2.048e+01 4.329e+00  -4.732 2.56e-06
candidate_nameMarco Rubio               -5.476e+00 5.477e+00  -1.000  0.31764
candidate_nameMark Cuban                -3.862e+01 5.479e+00  -7.048 3.47e-12
candidate_nameMatthew David McConaughey -2.772e+01 5.475e+00  -5.063 4.96e-07
candidate_nameMichelle Obama             2.929e+00 4.471e+00   0.655  0.51260
candidate_nameMike Pence                -3.803e+00 4.139e+00  -0.919  0.35837
candidate_nameMike Pompeo               -1.048e+01 5.477e+00  -1.913  0.05607
candidate_nameMitt Romney               -9.476e+00 5.477e+00  -1.730  0.08392
candidate_nameNikki Haley               -3.684e+00 3.932e+00  -0.937  0.34904
candidate_namePete Buttigieg             1.282e+00 4.329e+00   0.296  0.76713
candidate_nameRandall A. Terry          -4.238e+01 4.082e+00 -10.382  < 2e-16
candidate_nameRaphael Warnock           -2.232e+00 5.475e+00  -0.408  0.68355
candidate_nameRick Scott                -9.476e+00 5.477e+00  -1.730  0.08392
candidate_nameRobert F. Kennedy         -3.351e+01 3.889e+00  -8.615  < 2e-16
candidate_nameRon DeSantis              -1.840e+00 3.897e+00  -0.472  0.63686
candidate_nameShiva Ayyadurai           -4.179e+01 4.471e+00  -9.347  < 2e-16
candidate_nameTaylor Swift              -1.594e+01 5.477e+00  -2.911  0.00368
candidate_nameTed Cruz                  -1.174e+01 4.742e+00  -2.476  0.01347
candidate_nameTim Scott                 -6.174e+00 4.106e+00  -1.503  0.13304
candidate_nameTom Cotton                -1.148e+01 5.477e+00  -2.095  0.03640
candidate_nameVivek G. Ramaswamy        -1.158e+01 4.107e+00  -2.820  0.00490
week                                     2.440e-09 1.232e-09   1.981  0.04792

(Intercept)                             ***
candidate_nameAndy Beshear
candidate_nameBernie Sanders
candidate_nameChase Oliver              ***
candidate_nameChris Christie            .
candidate_nameChris Sununu
candidate_nameClaudia De La Cruz        ***
candidate_nameCornel West               ***
candidate_nameDonald Trump
```

```
candidate_nameElizabeth Ann Warren
candidate_nameGavin Newsom
candidate_nameGlenn Youngkin
candidate_nameGretchen Whitmer
candidate_nameHillary Rodham Clinton
candidate_nameJ.B. Pritzker
candidate_nameJerome Michael Segal
candidate_nameJill Stein                ***
candidate_nameJoe Biden
candidate_nameJoe Manchin, III          ***
candidate_nameJoel Skousen              ***
candidate_nameJoseph Kishore            ***
candidate_nameJosh Hawley               *
candidate_nameJosh Shapiro
candidate_nameKamala Harris
candidate_nameKanye West                ***
candidate_nameKristi Noem               *
candidate_nameLarry Hogan               **
candidate_nameLars Mapstead             ***
candidate_nameLiz Cheney                ***
candidate_nameMarco Rubio
candidate_nameMark Cuban                ***
candidate_nameMatthew David McConaughey ***
candidate_nameMichelle Obama
candidate_nameMike Pence
candidate_nameMike Pompeo               .
candidate_nameMitt Romney               .
candidate_nameNikki Haley
candidate_namePete Buttigieg
candidate_nameRandall A. Terry          ***
candidate_nameRaphael Warnock
candidate_nameRick Scott                .
candidate_nameRobert F. Kennedy         ***
candidate_nameRon DeSantis
candidate_nameShiva Ayyadurai           ***
candidate_nameTaylor Swift              **
candidate_nameTed Cruz                  *
candidate_nameTim Scott
candidate_nameTom Cotton                *
candidate_nameVivek G. Ramaswamy        **
week                                    *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for gaussian family taken to be 14.98812)

    Null deviance: 374459  on 1005  degrees of freedom
Residual deviance:  14329  on  956  degrees of freedom
AIC: 5629.1

Number of Fisher Scoring iterations: 2
```

4 Results

Our results indicate several trends in the polling data. Below, we summarize key findings from the GLM analysis.

```
              candidate_name predicted_support
33            Michelle Obama        42.2370809
24             Kamala Harris        41.7453832
3             Bernie Sanders        41.7446129
12            Glenn Youngkin        41.4469587
6               Chris Sununu        41.2419408
10      Elizabeth Ann Warren        40.9212110
38            Pete Buttigieg        40.5906184
11              Gavin Newsom        40.3953951
9               Donald Trump        40.2090176
13          Gretchen Whitmer        40.0284929
14    Hillary Rodham Clinton        39.5662095
18                 Joe Biden        39.5250188
1                    Al Gore        39.3084212
23              Josh Shapiro        38.5239547
15             J.B. Pritzker        38.0884377
43              Ron DeSantis        37.4682741
40           Raphael Warnock        37.0759547
16      Jerome Michael Segal        36.8914859
37               Nikki Haley        35.6247021
34                Mike Pence        35.5051985
30               Marco Rubio        33.8324558
47                 Tim Scott        33.1346467
5             Chris Christie        31.3094289
2               Andy Beshear        30.4199813
36               Mitt Romney        29.8324558
41                Rick Scott        29.8324558
```

```
35               Mike Pompeo        28.8324558
48                Tom Cotton        27.8324558
22               Josh Hawley        27.8324558
26               Kristi Noem        27.8324558
49        Vivek G. Ramaswamy        27.7259525
46                  Ted Cruz        27.5700517
27               Larry Hogan        24.8324558
45              Taylor Swift        23.3652018
29                Liz Cheney        18.8259114
32 Matthew David McConaughey        11.5900903
42         Robert F. Kennedy         5.8006116
25                Kanye West         3.3652018
19          Joe Manchin, III         2.5522043
31                Mark Cuban         0.6907838
28             Lars Mapstead        -1.2527890
17                Jill Stein        -1.4580239
8                Cornel West        -1.4760676
7         Claudia De La Cruz        -2.0332494
4               Chase Oliver        -2.1375977
44           Shiva Ayyadurai        -2.4844102
39          Randall A. Terry        -3.0713314
20              Joel Skousen        -3.0908051
21            Joseph Kishore        -3.0967081
```

Based on the forecasted support levels from our model, Michelle Obama is projected to have the highest support on election day, with an estimated 46.46% of the vote, followed closely by Kamala Harris and Bernie Sanders, each with approximately 45.97% support. This preliminary forecast, derived from aggregated polling data and sample size weighting, offers an insight into the relative standings of the candidates.

4.1 Interpretation of Results

Overall Support Trends: The coefficient for week in our model is positive, suggesting a slight upward trend in aggregate support over time. Candidate-Specific Effects: Certain candidates, such as Chase Oliver and Cornel West, show large negative coefficients, indicating significantly lower support relative to other candidates. Forecast Implications: Our model suggests that Michelle Obama, Kamala Harris, and Bernie Sanders are strong contenders if these trends persist through to the election. Adjustments, such as incorporating recent polling data or state-specific analysis, may refine these forecasts.

5 Discussion

5.1 Key Findings

In this section, we discuss the implications of our model results and provide a deeper analysis of the election forecasting results.

5.1.1 First Discussion Point: Insights from Candidate Support Trends

Our model shows that candidates such as Michelle Obama, Kamala Harris, and Bernie Sanders have high predicted support, with Michelle Obama leading the projections. This suggests that these candidates may have broader appeal or consistent support across polls. Analyzing these trends provides insights into voter preferences and candidate standing leading up to the election. The trend of rising support for these top candidates could indicate either a solidifying base or increased media coverage that positively impacts their polling numbers.

5.1.2 Second Discussion Point: The Impact of Sample Size on Prediction Accuracy

The LOESS smoothed support trends show that sample size plays a significant role in the accuracy and stability of polling results. Candidates with consistent polling across larger sample sizes, such as Joe Biden and Donald Trump, display more stable support trends. In contrast, candidates with smaller or inconsistent polling samples exhibit greater variability, which may introduce noise into the forecasting model.

5.1.3 Third Discussion Point: Candidate-Specific Variations and Regional Differences

Our model reveals that certain candidates have regionally concentrated support, which contributes to variability in their polling results. For example, some candidates have outliers in their polling data, potentially due to strong localized support in specific states. Understanding these regional effects can help refine future election models to account for geographical biases in polling data.

5.1.4 Weaknesses and Next Steps

5.1.4.1 Weaknesses

1. **Data Limitations**: The reliance on historical polling data introduces a potential bias, especially for candidates with limited polling information. Candidates with fewer polls may not have representative support, which could skew our predictions.

2. **Model Assumptions**: The model assumes that support trends remain stable over time. However, election dynamics can change rapidly, influenced by unforeseen events or shifts in public opinion.
3. **Aggregated National Data**: Our model uses aggregated polling data rather than state-specific polls, which may overlook important regional variations in support. This could lead to less accurate predictions for the Electoral College outcome.

5.1.4.2 Next Steps

1. **Incorporate State-Level Polling**: Adding state-specific polling data could improve the accuracy of the model, especially in predicting Electoral College outcomes.
2. **Explore Nonlinear Models**: Given the dynamic nature of elections, nonlinear models or time-series models (e.g., ARIMA, Bayesian hierarchical models) could better capture sudden changes in support.
3. **Increase Sample Size for Low-Support Candidates**: To ensure a comprehensive analysis, future studies could focus on obtaining more polling data for lesser-known candidates to improve the robustness of the model.

Appendix

5.1 Additional Data Details

Here we provide additional context on the dataset used in this analysis, including information about the variables and data processing steps.

5.1.1 Data Processing

The data processing steps involved cleaning the dataset by removing columns with excessive missing values, filtering out polls with non-representative sample sizes, and aggregating the data to a weekly level.

```
Rows: 16,776
Columns: 11
$ poll_id        <dbl> 89083, 89083, 89112, 89112, 89112, 89112, 89112, 89090,~
$ pollster       <chr> "SoCal Strategies", "SoCal Strategies", "St. Anselm", "~
$ start_date     <chr> "10/28/24", "10/28/24", "10/28/24", "10/28/24", "10/28/~
$ end_date       <chr> "10/29/24", "10/29/24", "10/29/24", "10/29/24", "10/29/~
$ sample_size    <dbl> 600, 600, 2791, 2791, 2791, 2791, 2791, 1302, 1302, 130~
$ population     <chr> "lv", "lv", "lv", "lv", "lv", "lv", "lv", "lv", "lv", "~
$ methodology    <chr> "Online Panel", "Online Panel", "Text-to-Web", "Text-to~
$ candidate_name <chr> "Kamala Harris", "Donald Trump", "Kamala Harris", "Dona~
$ pct            <dbl> 49.0, 49.0, 51.0, 46.0, 1.0, 0.0, 0.0, 48.3, 47.5, 1.1,~
$ party          <chr> "DEM", "REP", "DEM", "REP", "LIB", "IND", "GRE", "DEM",~
$ state          <chr> "Wisconsin", "Wisconsin", "New Hampshire", "New Hampshi~
```

Alexander, Rohan. 2023. *Telling Stories with Data*. Chapman; Hall/CRC. https://tellingstorieswithdata.com/.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.