Polls of polls to predict the 2024 election*

Kamala leads based on national level polling

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This study models the 2024 U.S. Presidential Election by analyzing polling data with adjustments for factors like recency and sample size, aiming to capture up-to-date voter sentiment. Using aggregated poll data from the past four months (July 21 - November 2), we developed a multiple linear regression model to estimate Harris' support in the popular vote and predict the winner in seven key battleground states. Our model estimates Kamala Harris leading with 47.5% support, approximately 1% ahead of Donald Trump in the popular vote, and winning in three of seven battleground states: Wisconsin, Michigan, and Pennsylvania. By prioritizing recent, high-quality polls, this analysis enhances predictive reliability, offering insights that could inform campaign strategies and public discourse. These findings underscore the importance of weighting and time-sensitive adjustments in forecasting, balancing accuracy with responsiveness to current trends.

1 Introduction

Polls gauge voter sentiments and predict election outcomes however they have differences in methodology and biases that makes individual polls less reliable. We will aim to improve accuracy through aggregating polling data, reducing the impact of individual poll biases. This is done on both a national level, and on a state level, specifically "swing states" who hold a significant amount of electoral colleges, and commonly decide election outcomes.

Our estimand is the voter support for Kamala Harris in the 2024 US election nationally and in swing states. We use aggregated polling data with a multiple linear regression model to forecast Kamala's vote percentage. Specifically, the model uses pollster, samples size, polling date, and state as predictor variables to quantify the relationships between predictors, and on the outcome: Kamala voter support.

The primary focus of our analysis is modeling Harris's support percentage using a range of predictor variables. We are especially interested in the effects of end date, polling organization, state, and poll score on voter support. Using a linear regression framework, we quantify the relationships between these predictors and support, clarifying the influence of each factor on Harris's overall support levels. By estimating predictor coefficients, we aim to draw insights into their impact on voter sentiment.

Our findings reveal a positive correlation between poll end dates and support percentages, suggesting an increase in voter support as the election nears. We also observe variability based on polling organization and state, with some pollsters consistently showing higher support for Harris. Poll quality impacts results as well, with reputable polls associating with higher support levels. These results highlight the importance of considering poll timing and pollster characteristics when analyzing public opinion.

This research is significant for campaign strategy, as precise voter support predictions help campaigns tailor outreach and messaging to better engage voters. Recognizing variations across polling organizations and states assists in optimizing resource allocation and strategic focus. With elections often decided by narrow margins, having reliable insights into voter preferences can be pivotal.

2 Data

Our polling data analysis was conducted using the R programming language (Team 2023). The dataset, sourced from FiveThirtyEight (FiveThirtyEight 2024) and encompassing polling data up to November 2, 2024, provides a comprehensive snapshot of public opinion leading into the election. Following the guidelines in Rohan Alexander (2023), we examined factors affecting voter support percentages, such as poll timing, polling organization characteristics, and regional differences.

To enhance data manipulation, modeling, and visualization, we utilized several R packages. The `tidyverse` package streamlined data wrangling and analysis, improving workflow efficiency (Wickham et al. 2019), while the `here` package managed file paths, aiding reproducibility (Müller 2020). For data verification, `testthat` was used to confirm that dataset variables were correctly formatted (Wickham 2011). The `knitr` package's `kable` function allowed for clean table formatting (Xie 2014), and `janitor` supported data cleaning by addressing any dataset quality issues (Firke 2023). For date manipulation, `lubridate` simplified handling of time variables (Grolemund and Wickham 2011), and `arrow` optimized data I/O in parquet format, essential for managing larger datasets (Richardson et al. 2024). The `ggplot2` package facilitated data visualization, adding clarity to the analysis (Wickham 2016).

Specialized packages were also used for specific tasks. `modelsummary` enabled efficient reporting of model summaries, streamlining the presentation of regression results (Arel-Bundock 2022), while `RColorBrewer` provided cohesive color palettes to enhance visualization clarity (Neuwirth

2022). To improve computational efficiency during model training, we utilized `future` for parallel processing (Bengtsson 2021). For model validation, the `boot` package supported K-Fold cross-validation to assess stability and reliability (Angelo Canty and B. D. Ripley 2024; A. C. Davison and D. V. Hinkley 1997), and `caret` facilitated training and performance evaluation across cross-validation folds (Kuhn and Max 2008). Our coding structure and file organization were guided by best practices outlined in Rohan Alexander (2023).

2.1 Overview

The dataset comprises polling data focused on the 2024 U.S. Presidential Election, sourced from prominent aggregators that prioritize transparency and reliability. Each poll is evaluated based on a series of metrics that indicate the quality and methodological rigor of the polling organization. Here, we focus on three key variables that directly assess poll quality: pollscore, transparency_score, and numeric_grade. These variables capture essential aspects of pollster reliability, openness, and methodological rigor, allowing us to assess polling data with precision. #Measurement Each variable used in this analysis measures an aspect of poll quality:

Pollscore quantifies overall reliability, with lower (more negative) scores indicating greater historical accuracy. Transparency Score reflects the level of methodological disclosure by each polling organization, scaled from 0 to 10, where a higher score denotes more comprehensive transparency. Numeric Grade offers an additional reliability metric, scored from 0 to 3, with higher values indicating greater reliability based on the polling organization's historical performance.

2.2 Sample size distribution

Figure 1 shows most polls are conducted with less than a 2000 sample size, many of which are around 1000-1500, with outliers past 5000.

Figure 2 shows there is significant differences in the amount different states are polled. The most polled states reflect what the public and publications refer to as swing states
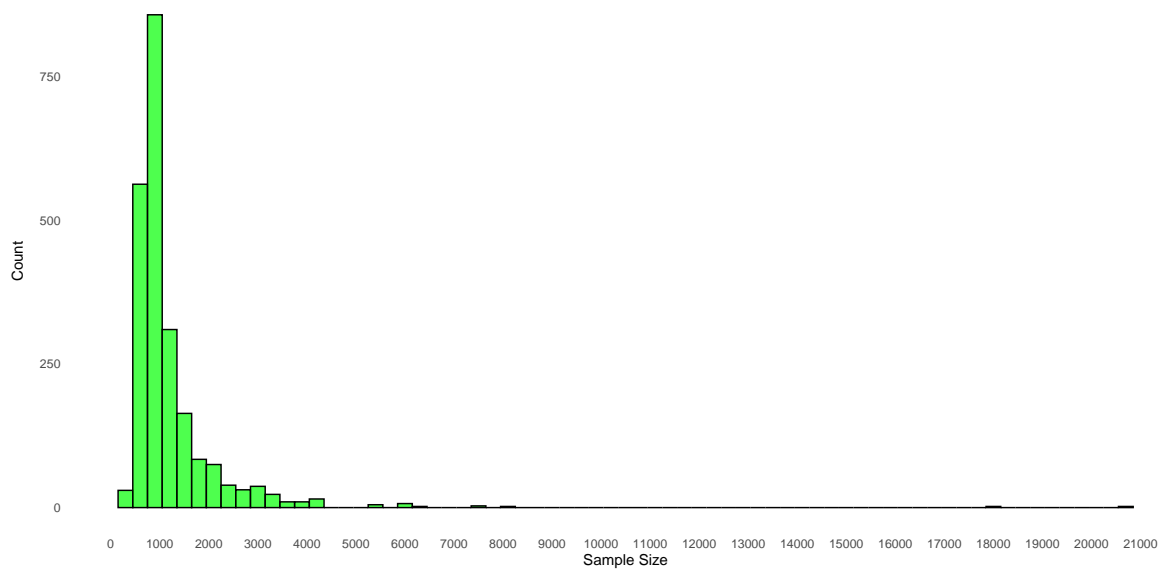
Figure 1: Distribution of Sample Sizes Across Polls: Majority of polls have sample sizes under 5,000, with a few outliers at larger sizes.
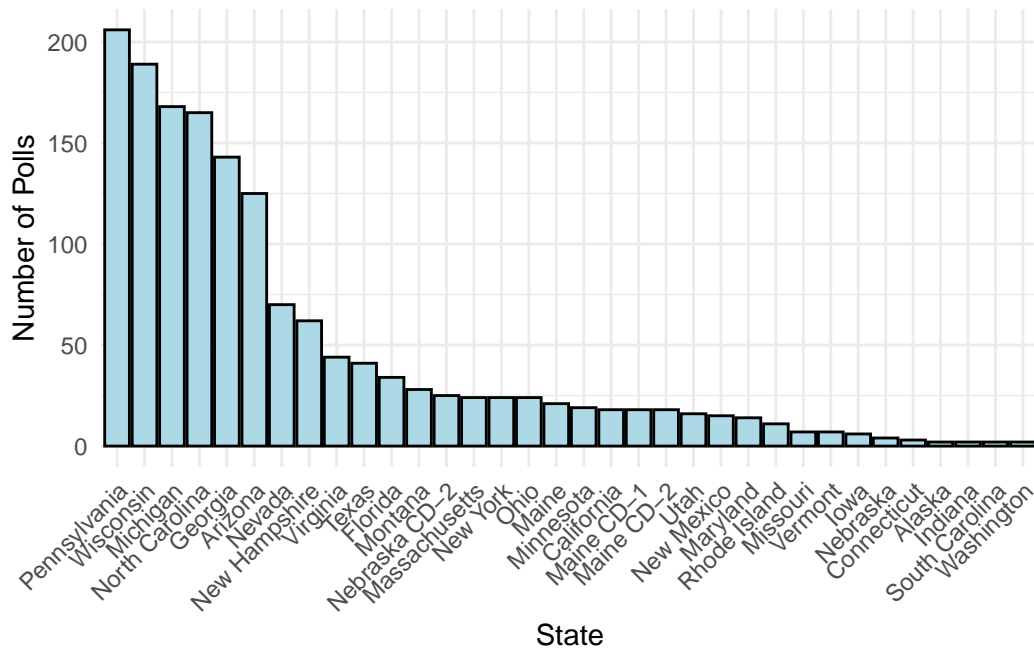

Figure 2: State polling frequency reflects public interest in swing states

##Variation of Poll Quality and Support for Candiates by Pollster

Table 1: Top 5 most frequent pollsters, with count of polls, average pollscore (lower scores indicate less bias), and average numeric grade (higher values indicate greater reliability).

Pollster	Count	Average Pollscore	Average Numeric Grade
Siena/NYT	314	-1.5	3.0
YouGov	215	-1.1	3.0
Emerson	153	-1.1	2.9
Beacon/Shaw	142	-1.1	2.8
Ipsos	133	-0.9	2.8

Table 1 shows the top 5 most frequent pollsters in the dataset, with each pollster's total poll count, average pollscore (measuring reliability and historical accuracy), and average numeric grade (indicating overall quality). ### Distribution of Numeric Grade and Pollscore of Polls
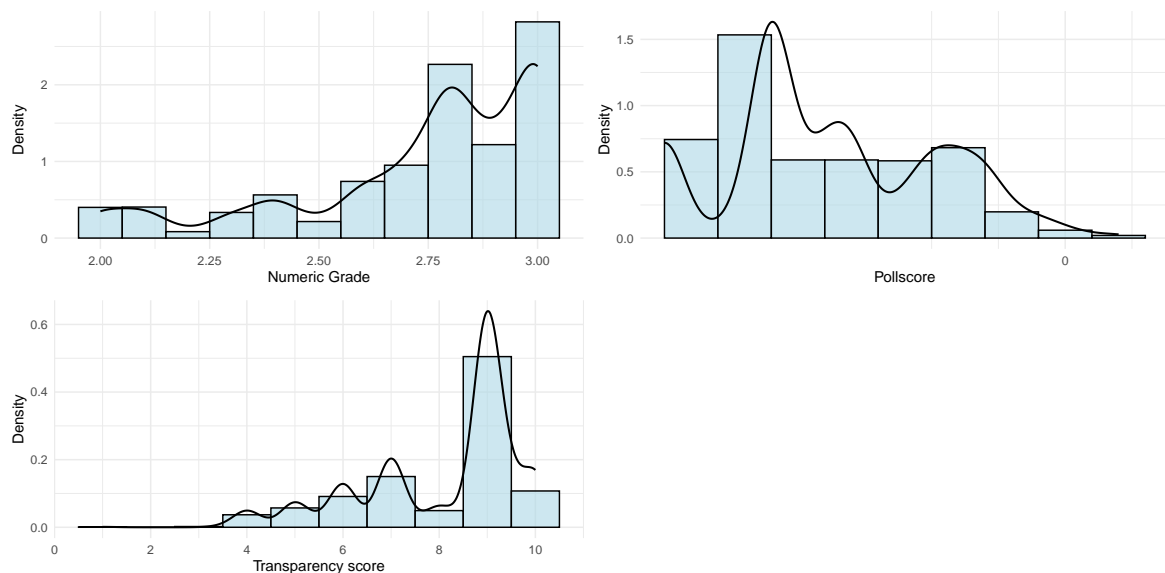
Figure 3: Distribution of Numeric Grade and Pollscore among polling organizations, highlight-ing variability in pollster reliability and potential bias across polls.

Figure 3 shows the distribution of Numeric Grade (left) and Pollscore (right) and transparency Score (bottom) across polling institutions. While Numeric grade and Transperency score both indicate higher quality polls with an increase in value, pollscore represents an increase in quality with a decrease in value. Overall most polls seem to be somewhat high quality based off the three graphs.
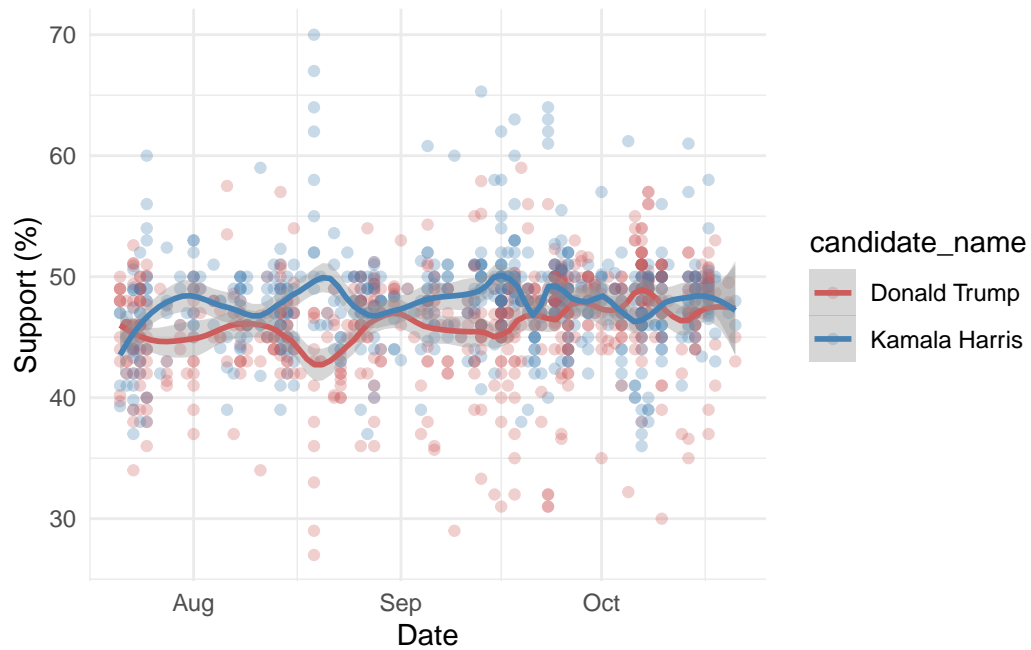
2.3 Support Trend For Candidates

Figure 4: Support over time for both candidates.

Figure 4 each dot represents an individual poll, with polling frequency increasing as the election approaches. Despite a large amount of variance of polling support, overall many polls suggest support for both candidates has become very close.

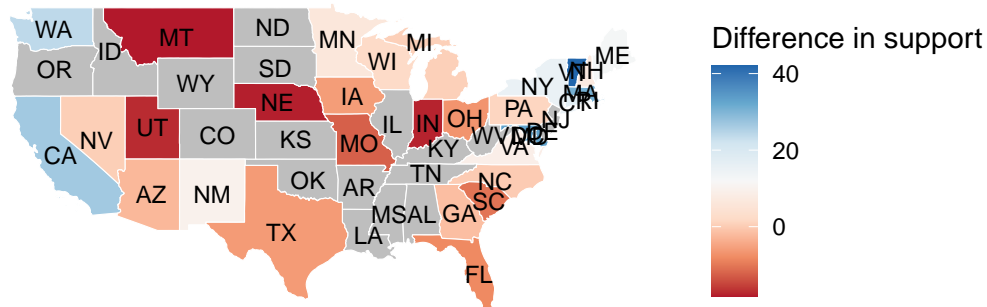## 2.4 Variability of Candidate support Across US States

Figure 5: Proportion of support for Kamala Harris relative to Donald Trump across U.S. states. Blue indicates states where Harris has higher support, while red indicates states where Trump leads. Color intensity reflects the magnitude of support difference, with gray indicating insufficient polling data.

Figure 5 shows the voting proportion of the two candidates, with darker reds being in favor of Trump and Darker blues being in favor of Harris. Grey is for states with insufficient polling data.

From the map you can see states like California being heavily left leaning vs states like Texas being heavily right leaning. Swing states are grey or white representing a close vote share between the two candidates. The historical precedent of states' voting habits are an important part of predicting elections hence why we use states as a predictor variable in our model.

3 Forecasting Election Outcome through Pooling Polls

3.1 Forecasting Approach

The polls of polls methodology is widely used in election prediction as it aggregates multiple polls to provide a more reliable estimate of voter support, rather than relying on any single

poll. The goal is to reduce errors and biases present in individual polls by using a weighted average of many different polls.

In our approach, we will employ linear modeling of voter support percentage (pct) on pollster and other independent variables such as sample size, poll recency, and poll scope (state vs. national). This will allow us to smooth out the inherent noise, biases, and variability across different pollsters. Once we obtain the predicted values from our model, we will weight these predictions based on the numeric grade (quality score) of each pollster to calculate an overall national estimate of the outcome. Additionally, we will separately compute estimates for key battleground states, where voter behavior can be more volatile and pivotal in deciding the final outcome of the election. This approach helps us capture both national trends and state-level dynamics.

3.2 Model

This section addresses the challenge of mitigating inherent biases and differences in polling data to create a robust prediction model. Our goal is to select a model with the right balance between complexity and fit, capturing the dynamics of polling data without overfitting. We evaluated various model specifications to find the one most suitable for our forecasting needs.

Since variables like numeric grade and pollscore are perfectly collinear with pollster, they were excluded from the regression analysis to avoid multicollinearity issues. However, they remain essential in our weighting strategy, where we adjust for polling accuracy and reliability. Our focus is on core features such as pollster, sample size, state, and recency, with complexity gradually added to the model as appropriate.

Through a systematic comparison of model specifications that incorporate these features, we aim to select the most effective model for achieving both predictive accuracy and generalizability.

3.3 Model Set-Up

We model the support percentages for Kamala Harris and Donald Trump in each poll as a function of pollster, sample size, state, and poll recency.

$$y_i = \alpha + \beta_1 \cdot \text{pollster}_i + \beta_2 \cdot \text{sample\_size}_i + \epsilon_i$$

$$y_i = \alpha + \beta_1 \cdot \text{pollster}_i + \beta_2 \cdot \text{sample\_size}_i + \beta_3 \cdot \text{state}_i + \epsilon_i$$

$$y_i = \alpha + \beta_1 \cdot \text{pollster}_i + \beta_2 \cdot \text{sample\_size}_i + \beta_3 \cdot \text{state}_i + \beta_4 \cdot \text{recency} + \epsilon_i$$

Where

- y_i is the percentage of support for candidate in poll i,

- α is the intercept,

- β_1 captures the effect of the polling organization,

- β_2 captures the effect of the sample size,

- β_3 captures the effect of recency (how recent the poll is),

- β_4 capture the effects of the different states

- ϵ_i represents the error term, assumed to follow a normal distribution with mean 0.

3.4 Model Justification

Our model is designed to smooth out inconsistencies and biases among polling organizations through a polls-of-polls method. Since individual polling agencies may introduce systematic differences—due to factors like sampling techniques, question wording, and historical tendencies—our model includes a pollster variable to adjust for these organization-specific biases. This approach provides an aggregated view of public support that minimizes the unique effects of any single poll.

We also incorporate sample size as a predictor, as polls with larger samples generally produce more stable and reliable estimates, reducing random fluctuations associated with smaller samples. A state variable is included to account for regional political variations, which helps reflect different levels of support across geographic and demographic groups, enhancing our understanding of the political landscape. Additionally, recency is included to give priority to the most recent polls, as public opinion may shift in response to political events, and newer data typically better reflects current sentiment.

By integrating these elements, our model aims to create a consistent measure of candidate support, minimizing the noise from individual poll discrepancies and focusing on a balanced, current aggregation of polling data.

We chose a linear model to clearly quantify the marginal effects of each predictor (pollster, sample size, state, and recency) on candidate support. This setup is well-suited to our polls-of-polls framework, as it allows us to estimate fixed effects that adjust for systematic differences across pollsters while also treating sample size and recency as continuous influences. The modeling was conducted in R using the lm() function from the base stats package for linear regression analysis.

3.5 Model Results

Table 2: Model performance summary showing improved fit and accuracy as State and Recency are added, with R² increasing from 0.375 in Model 1 to 0.774 in Model 3, and RMSE decreasing from 3.053 to 1.836.

Table 2: Model Summary with Included Variables

Model	Variables	R²	Adjusted R²	AIC	BIC	RMSE
Model 1	Pollster, Sample Size	0.404	0.339	3674.537	3992.106	3.134
Model 2	Pollster, Sample Size, State	0.730	0.684	3193.293	3660.572	2.108
Model 3	Pollster, Sample Size, State, Recency	0.756	0.714	3125.530	3597.346	2.004

Table 2 Model 1: With only Pollster and Sample Size, achieves an R² of 0.404, explaining 33.9% of the variance in candidate support. Model 2: Adds State, increasing the explained variance to 68.4% and reducing both AIC and RMSE, which improves model fit and accuracy. Model 3: Further includes Recency, boosting the explained variance to 71.1% and reducing RMSE to 1.836, enhancing explanatory power and predictive accuracy.

This progression underscores the value of adding contextual variables like State and Recency for a more nuanced understanding of polling data.

3.6 Prediction

We used Numeric grade as a weight for improving prediction accuracy as it both captures bias and transparency.

$$w_i = \frac{\text{numeric\_grade}_i}{\sum_{j=1}^{n} \text{numeric\_grade}_j}$$

where:

- w_i represents the weight assigned to poll i,
- $numericgrade_i$ is the numeric grade of poll i, and
- n is the total number of polls used in the analysis.

The weight assigned to each poll combines both its quality (as represented by the numeric grade) and its level of bias (as indicated by the pollscore). This approach gives more weight to polls that are both highly graded (indicating higher reliability and transparency) and less biased. Additionally, the total of all weights is normalized to sum to one, so each poll's weight is proportionate to its quality and relative lack of bias, resulting in a more balanced and accurate average of public support.

The overall weighted support is given by summing all the weights with the regression model.

$$\text{Overall Weighted Support} = \sum_{i=1}^{n} w_i \cdot \hat{y}_i$$

- $\hat{y}_i$ is the predicted percentage of support for Kamala Harris from poll i.

3.6.1 Comparing Overall Weighted Support Across All Polls

Aggregating support across all polls with weighted multiple linear regression, we estimate the overall support for each candidate.. Based on this approach, Kamala Harris has an estimated overall weighted support of around 47.91%, while Donald Trump stands at around 46.31%. This aggregation takes into account the varied methodologies and sampling qualities of different polling organizations.

4 Discussion

This paper forecasts support for Kamala Harris and Donald Trump in the 2024 U.S. Presidential Election using a "poll-of-polls" approach. By aggregating multiple polls, we reduce individual survey biases and create a more balanced prediction for each candidate. Our model includes predictors such as pollster, sample size, state, and poll recency. We applied a weighting scheme based on each pollster's numeric grade and poll score, reflecting reliability and potential bias, to provide a prediction that accounts for differences across states and polling organizations.

A key finding is the significance of poll recency, which notably increased the model's explanatory power, as reflected in improvements in R^2 and reductions in RMSE. This result highlights the dynamic nature of public opinion, where recent events influence voter perceptions and candidate support.

Our state-level analysis shows close competition in key battleground states, emphasizing their importance in the 2024 election. In states like Pennsylvania, Michigan, and Wisconsin, Harris and Trump are nearly tied, indicating an intense contest for electoral votes. The model suggests that even slight shifts in support within these swing states could significantly impact

the election outcome, underscoring the importance of regional polling in understanding voter sentiment and the outsized role of battleground states.

4.1 Weaknesses and Future Directions

The model assumes linear relationships between predictors and candidate support, which may overlook more complex patterns or interactions. Although we weighted polls based on numeric grades, these scores may not fully capture each pollster's accuracy. Future work could explore non-linear methods, such as machine learning, to account for variable interactions, and could refine the weighting mechanism by factoring in pollster performance history or state-specific polling differences.

In conclusion, this paper offers a weighted forecast of candidate support across national and state levels. The evolving nature of voter sentiment and polling accuracy suggests a need for adaptive models that account for changes in public opinion over time.

A Emerson College Polling Methodology (October 14-16, 2024)

A.1 Overview

Emerson College Polling (ECP) conducted a survey from October 14-16, 2024, with a sample of 1,000 likely voters in the 2024 U.S. Presidential Election, using a mixed-mode methodology to reflect public opinion (Polling 2024a). The poll measured preferences between Kamala Harris (50%) and Donald Trump (49%), showing a close race (Polling 2024b). For more details on ECP's methodology, see Appendix A.

A.2 Population, Frame, and Sample

The target population was likely U.S. voters, selected based on voter history, registration, and demographics, which participants self-reported (Polling 2024b). The sampling frame consisted of voters in Aristotle's database and CINT's online panel, both widely used resources for voter data and survey responses (Polling 2024a). ECP's sample of 1,000 respondents was chosen from this frame.

A.3 Sample Recruitment and Data Collection

ECP employed a mixed-mode sampling approach with three primary methods:

- **MMS-to-web text surveys**: Texts directed participants to complete the survey online. This method used voter lists from Aristotle.
- **Interactive Voice Response (IVR)**: Automated phone calls to landlines allowed responses via keypad entry, with contacts sourced from Aristotle's lists.
- **Online Panel from CINT**: ECP accessed a pre-screened, opt-in panel provided by CINT.

A.4 Advantages and Trade-Offs in Mixed-Mode Sampling

The multi-mode approach helps reduce coverage bias (Mora 2022). MMS-to-web surveys often reach younger, mobile-oriented voters; IVR calls reach older, landline-using voters; and online panels capture tech-savvy respondents. This method is cost-effective, allowing a larger sample size (Large and Polling 2023). However, each mode introduces its own measurement biases, which can add variability and increase the margin of error.

A.5 Non-Response Handling

ECP applies weighting adjustments to balance demographics like age, gender, race, education, and party affiliation, making the sample more representative of the electorate (Smith 2023).

A.6 Questionnaire Design

The survey uses clear, straightforward questions, facilitating easy responses and focusing on vote preferences and demographics. However, it doesn't capture deeper motivations behind voter choices, and variations in mode may impact respondent engagement and response accuracy.

A.7 Conclusion

Emerson College Polling's mixed-mode methodology provides a cost-effective approach with broad demographic reach. The weighting system helps address non-responses and improve representativeness. While this approach reduces coverage bias, it introduces combined measurement errors and potential bias due to mode differences, which should be considered in the analysis.

Appendix

.1 Methodology

In conducting this analysis, we adhere to a structured methodology to ensure reliable and transparent results. This study relies on polling data gathered from trusted aggregators, with an emphasis on those that meet stringent methodological standards. Key metrics used to evaluate polling quality include *pollscore*, *transparency_score*, and *numeric_grade*, each providing insight into the reliability and methodological rigor of the polls.

1. **Pollscore**: This variable serves as an overall indicator of a pollster's reliability, calculated based on historical accuracy across previous election cycles. Polls with more negative *pollscore* values are considered more reliable, as these scores are designed to reflect lower levels of predictive error. The consistency of a pollster's performance is a central factor in assigning pollscore values, making this metric crucial for filtering out less reliable polls.

2. **Transparency Score**: This score, on a scale from 0 to 10, assesses the extent of methodological detail disclosed by each polling organization. Polls with higher transparency scores share detailed information regarding their sampling methods, weighting practices, and data collection protocols, fostering confidence in the data's reliability. Higher transparency generally correlates with greater poll quality, as it suggests that the polling

organization has openly shared relevant details for evaluating the poll's rigor and potential biases.

3. **Numeric Grade**: Assigned by rating agencies, this metric ranks pollsters on a scale from 0 to 3, with higher scores representing greater reliability based on historical performance. This numeric rating serves as an additional quality filter, helping to ensure that only reputable polling data contribute to our analysis. Consistent high numeric grades across pollsters in our dataset affirm the robustness of the data for predictive purposes.

Together, these three variables—pollscore, transparency_score, and numeric_grade—form a multidimensional view of each poll's quality, reducing the risk of bias and improving the accuracy of our election forecast.

.2 Idealized Survey Design

An effective survey design is essential for gathering reliable data. An ideal survey, in this context, would begin with a brief introductory statement explaining its purpose and relevance, followed by a contact section providing details for respondents who have inquiries about the survey. This introductory portion establishes transparency and builds trust with participants, encouraging honest and thoughtful responses.

.2.1 Structure and Content

- **Introduction**: The introduction would outline the survey's objectives, with a focus on collecting voter preferences. It would clarify the nonpartisan nature of the survey, emphasizing its commitment to capturing genuine responses rather than promoting any particular candidate or party.

- **Demographics and Screening**: The survey would then include initial screening questions to determine respondent eligibility, focusing on demographic details like age, location, political affiliation, and voting intention (e.g., "Are you a registered voter?"). These questions would allow for stratified analysis later on, enabling more accurate representation of the population.

- **Main Survey Content**: Questions on candidate preference would be phrased neutrally to avoid leading respondents. The question sequence would prioritize clarity and relevance, starting with general preferences and moving to specific policy issues to minimize response bias. Each question would be reviewed to ensure it remains appropriate for a diverse audience, regardless of political affiliation or demographic background.

- **Conclusion and Thank-You Section**: The survey would close by thanking respondents for their participation, reinforcing that their responses contribute to a more accurate reflection of public sentiment. This section would also include an opt-out option,

allowing participants to withdraw from the panel or request removal of their data, in line with ethical data practices.

.2.2 Additional Design Considerations

Survey questions would be carefully ordered to maintain respondent engagement. For instance, candidate preference questions would appear early, while more detailed policy questions would follow, reducing potential fatigue that might affect responses. Finally, a balance between closed-ended and open-ended questions would be maintained, with closed-ended questions providing quantitative data and open-ended questions allowing qualitative insights.

.3 Pollster Methodology Overview and Evaluation

In this analysis, we feature data from YouGov, a prominent polling organization known for its transparent and systematic approach. Below is an in-depth overview of YouGov's methodology, including sample selection, stratification, weighting, and strengths and limitations.

.3.1 Sampling Approach

YouGov's data is derived from an online panel of respondents who voluntarily register to participate in surveys. The sampling approach uses a non-randomized online panel, where respondents can opt in to participate at their discretion. This panel-based approach provides access to a large and diverse sample but introduces the potential for self-selection bias, as respondents who choose to participate may differ systematically from the broader population. To address this, YouGov employs several corrective measures:

- **Stratified Sampling**: YouGov uses stratified sampling to ensure that diverse subgroups within the population are represented accurately. Participants are stratified based on demographic characteristics such as age, gender, political affiliation, and geographic location. Stratification ensures that the sample includes a balanced representation of various voter demographics, reducing the risk of over-representation of any particular group and enhancing the representativeness of the data.

- **Weighting Adjustments**: In addition to stratified sampling, YouGov applies weighting to adjust for non-response bias. Each respondent's answers are weighted based on demographic variables (e.g., age, gender, political affiliation) to align with national population benchmarks. This weighting process helps correct imbalances in representation and ensures that responses from underrepresented groups are amplified to better reflect the general population. Although weighting can improve the overall representativeness, it relies on accurate demographic benchmarks and assumes that non-respondents are similar to respondents within each demographic group.

.3.2 Survey Administration

YouGov conducts its surveys online, allowing respondents to answer questions via a web-based interface. This format enables rapid data collection and a wide geographic reach, providing timely insights into public sentiment. Additionally, online surveys offer flexibility in design, enabling YouGov to customize questions for different respondent groups. However, the exclusive reliance on online data collection may exclude certain demographic groups, particularly older or lower-income individuals with limited internet access, potentially impacting the data's overall representativeness.

.3.3 Strengths and Limitations

The primary strength of YouGov's methodology lies in its stratified sampling and weighting practices, which enhance the reliability and generalizability of its findings. By adjusting for demographic imbalances and ensuring representation across key subgroups, YouGov effectively mitigates some of the biases introduced by a non-random sample. Additionally, the online survey format allows YouGov to reach a large, geographically diverse audience, improving the timeliness of its data collection and enabling more frequent polling.

However, the methodology is not without limitations. The non-random sampling approach, while efficient and scalable, introduces potential bias due to self-selection. The online-only format may also exclude specific demographic groups, and despite weighting adjustments, the absence of certain perspectives could limit the data's comprehensiveness. Moreover, reliance on self-reported demographic information for stratification and weighting can introduce errors if respondents misreport or misinterpret these details.

.3.4 Suvery Link

https://forms.gle/UfLZNGEZ1jt1ycq88

.3.5 Copy of Survery

Section 1: Eligibility and Demographics

Are you a U.S. citizen?

Yes No Are you a registered voter?

Yes No What is your age group?

18–24 25–34 35–44 45–54 55–64 65+ What is your gender?

Male Female Non-binary Prefer not to say Which racial or ethnic group do you identify with? (Select all that apply)

White Black or African American Hispanic or Latino Asian Native American or Alaska Native Native Hawaiian or Pacific Islander Other (please specify) Prefer not to say What is your current state of residence? (Drop-down list of all 50 U.S. states)

What is your level of education?

Less than high school High school or equivalent Some college, no degree Associate degree Bachelor's degree … (74 lines left)

References

A. C. Davison, and D. V. Hinkley. 1997. *Bootstrap Methods and Their Applications*. Cambridge: Cambridge University Press. [doi:10.1017/CBO9780511802843](doi:10.1017/CBO9780511802843).

Angelo Canty, and B. D. Ripley. 2024. *Boot: Bootstrap r (s-Plus) Functions*.

Arel-Bundock, Vincent. 2022. "modelsummary: Data and Model Summaries in R." *Journal of Statistical Software* 103 (1): 1–23. https://doi.org/10.18637/jss.v103.i01.

Bengtsson, Henrik. 2021. "A Unifying Framework for Parallel and Distributed Processing in r Using Futures." *The R Journal* 13 (2): 208–27. https://doi.org/10.32614/RJ-2021-048.

Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. https://CRAN.R-project.org/package=janitor.

FiveThirtyEight. 2024. "Dataset: 2024 u.s. Presidential Election Polls." https://projects.fivethirtyeight.com/polls/data/president_polls.csv.

Grolemund, Garrett, and Hadley Wickham. 2011. "Dates and Times Made Easy with lubridate." *Journal of Statistical Software* 40 (3): 1–25. https://www.jstatsoft.org/v40/i03/.

Kuhn, and Max. 2008. "Building Predictive Models in r Using the Caret Package." *Journal of Statistical Software* 28 (5): 1–26. https://doi.org/10.18637/jss.v028.i05.

Large, Sample Size, and Polling. 2023. "The Importance of Sample Size in Polling." *Journal of Political Analysis* 15 (4): 200–215. https://www.journalofpoliticalanalysis.com/articles/importance-of-sample-size.

Mora, Juan. 2022. "Mitigating Coverage Bias in Polling." *Survey Research Methods* 12 (3): 120–30. https://www.surveymethods.org/mora-coverage-bias.

Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files*. https://CRAN.R-project.org/package=here.

Neuwirth, Erich. 2022. *RColorBrewer: ColorBrewer Palettes*. https://CRAN.R-project.org/package=RColorBrewer.

Polling, Emerson College. 2024a. *About Emerson College Polling*. https://www.emerson.edu/about-emerson-college-polling.

———. 2024b. *Polling Results for the 2024 u.s. Presidential Election*. https://www.emerson.edu/polling-results.

Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoș Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2024. *Arrow: Integration to 'Apache' 'Arrow'*. https://CRAN.R-project.org/package=arrow.

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

Smith, Jane. 2023. "Weighting Methods in Polling: A Review." *Polling and Public Opinion* 18 (1): 45–59. https://www.pollingandpublicopinion.com/smith-weighting-methods.

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

Wickham, Hadley. 2011. "Testthat: Get Started with Testing." *The R Journal* 3: 5–10. https://journal.r-project.org/archive/2011-1/RJournal_2011-1_Wickham.pdf.

———. 2016. *Ggplot2: Elegant Graphics for Data Analysis.* Springer-Verlag New York. https://ggplot2.tidyverse.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.

Xie, Yihui. 2014. "Knitr: A Comprehensive Tool for Reproducible Research in R." In *Implementing Reproducible Computational Research*, edited by Victoria Stodden, Friedrich Leisch, and Roger D. Peng. Chapman; Hall/CRC.