Predicting the 2024 US Presidential Election with a Model-Based Forecast*

Using Generalized Linear Models to Predict Election Outcomes

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In this paper, we use a logistic regression model based on "poll-of-polls" data to predict the winner of the 2024 U.S. presidential election. By combining multiple polls, the model smooths out short-term fluctuations in surveys to make more reliable estimates of voter preferences. The findings show early trends in the leading candidates and reflect public opinion and its evolution through the election period. This prediction improves understanding of electoral trends and helps to explain the changing political scene more clearly.

1 Introduction

The presidential election has a significant impact on national and global policies, which makes election forecasting a valuable tool for understanding political outcomes. However, individual polls often contain biases and short-term fluctuations that can obscure long-term trends. To deal with these challenges, we use a 'poll-of-polls' approach that combines multiple polls to provide more stable predictions of voter preferences over time. In this paper, we use national polling data from the period leading up to the 2024 U.S. presidential election to generate a logistic model that predicts the winner while capturing changes in public opinion throughout the election period.

The model estimates the probability of a candidate winning an election based on aggregated polling data. Logistic regression is used for binary outcomes such as election results, which allows us to model the likelihood of each candidate winning as new data becomes available. By taking into account changes in opinion polls and tracking trends in public opinion over time, this model improves the accuracy of predictions.

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*Code and data are available at: [Forecasting the 2024 US Presidential Election](#).

Our analysis identifies key trends among the major candidates and tracks changes in public sentiment throughout the campaign. The results suggest that aggregated polls can reduce some uncertainty by smoothing short-term fluctuations between surveys, but uncertainty cannot be eliminated. A sudden change in public opinion can still change the path of an election campaign, which highlights the importance of continuous polling monitoring.

A reliable election forecast can influence public expectations, and campaign strategies, and increase the visibility of reporting on election trends. An accurate forecast can also increase voter participation by providing individuals with a clearer perspective of the electoral landscape, and help them participate more effectively in the process of democracy. Prediction models like ours not only help with resource allocation for campaigns but also support the wider public by providing them with a clearer understanding of political dynamics.

The structure of the paper is organized as follows: following Section 1, Section 2 presents the data collection and cleaning process, along with an overview of the variables used in the analysis. Section 3 introduces the forecasting models, explaining why the selected models are suitable for predicting election outcomes based on aggregated polling data. Then Section 4 presents the main findings, including detailed crime trends for each neighborhood and year. Finally, Section 5 provides the results, highlighting key trends and predictions. Eventuallt, Section 5 concludes with a discussion of the findings, evaluating the reliability of the forecasts and identifying potential limitations of the models.

2 Data

2.1 Overview

We use the statistical programming language R (R Core Team 2023) to process and analyze polling data for the 2024 US Presidential election. The data, obtained from a repository of publicly available polls, includes variables from numerous pollsters across the country (Ryan Best 2024). The aim is to create a reproducible forecast model by focusing on high-quality polls and narrowing our scope to Kamala Harris as a candidate of interest. Following methodologies discussed by "Telling Stories with Data" (Alexander 2023), we examine how polling data reflects electoral behavior and voter preferences.

The dataset includes 15,891 rows and 52 columns, covering various pollster attributes such as pollster name, state, methodology, and polling results. We filter the dataset to include only high-quality polls, i.e., those with a numeric grade of 3.0 or higher, ensuring that only reputable and well-documented pollster results are used in our model. Additionally, we focus solely on polls that include Kamala Harris as a candidate, which helps narrow our analysis to a specific electoral scenario.

2.2 Measurement

Polling data captures voter preferences and electoral forecasts by collecting responses from a representative sample of the population. In this case, pollsters attempt to gauge public opinion by surveying individuals on their preferred candidate, adjusting for demographic factors and political trends. The raw data entries reflect the outcomes of these surveys.

Pollsters often rely on random sampling methods to recruit participants, as discussed in [@ todo], ensuring a diverse and representative group. Some pollsters use online platforms, while others use phone interviews or in-person surveys. The dataset captures these variations through variables such as `methodology` and `sample_size`. Sampling errors, response biases, and adjustments (e.g., weighting respondents based on age, race, or geographic region) are part of how this world phenomenon is translated into data entries.

The process begins with identifying the population of interest—likely voters or registered voters—and applying statistical adjustments to the raw responses. Pollsters handle non-response through weighting or imputation methods, ensuring that missing data or low response rates do not skew the results significantly. The column `numeric_grade` reflects how well these pollsters adhere to rigorous methodology, allowing us to filter for only the most reliable sources in our analysis.

2.3 Outcome variables

2.3.1 Percent Support (pct)

The primary outcome variable in this dataset is the percentage of respondents who support a given candidate. This is represented by the pct variable, which is reported by pollsters for each candidate they survey. For Kamala Harris, this percentage reflects her standing in polls, and variations in this metric can indicate shifts in voter preference over time.

Below is a summary table showing the average, minimum, and maximum percent support for Kamala Harris across high-quality polls:

Some of our data is of penguins (Figure 1), from Horst, Hill, and Gorman (2020).

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.)
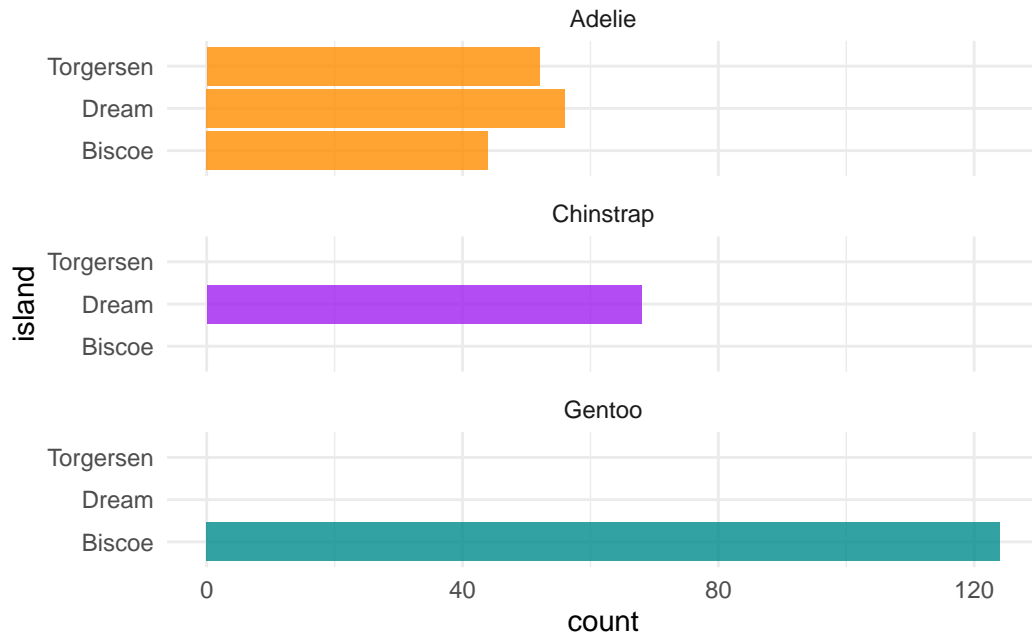
Talk way more about it.

Figure 1: Bills of penguins

2.4 Predictor variables

2.4.1 Pollster Name (display_name)

This variable represents the pollster responsible for each entry in the dataset. Different pollsters may use varying methods and possess differing levels of reliability, which the numeric_grade helps quantify. High-quality pollsters (numeric_grade 3.0) are emphasized in this analysis to ensure the robustness of the forecast.

2.4.2 Internal Polling (internal)

The variable internal is a binary indicator that identifies whether a poll was commissioned by a political campaign or interest group. Internal polls can sometimes be biased, either in how respondents are selected or how results are reported. However, the filtering for high-quality pollsters ensures that even internal polls meet certain standards of rigor.

2.4.3 Partisan Polling (partisan)

Like internal polling, partisan polling can introduce bias, as it may be sponsored by organizations with a vested interest in the election outcome. The partisan variable, similar to the

internal variable, flags such polls. In the dataset, these are rare but still important to identify, especially when making impartial predictions.

2.4.4 Party Affiliation (party)

The party variable indicates the political party that the poll respondent supports. This is key to understanding the partisan leanings of the sample. For Kamala Harris, her affiliation with the Democratic Party is represented in this column.

Below is a table summarizing the distribution of party affiliations in polls that include Kamala Harris:

2.4.5 Race ID (race_id)

This variable identifies the electoral race or contest being polled. In this analysis, the focus is on the 2024 presidential election. Tracking results across different races (i.e., primary versus general election) helps in understanding shifts in voter opinion throughout the campaign.

In summary, the dataset offers a rich variety of variables that capture voter sentiment, pollster reliability, and electoral dynamics. By carefully filtering and analyzing this data, we can build a robust model to forecast the outcome of the 2024 US Presidential election.

3 Model

Our modeling approach aims to quantify the relationship between polling characteristics and the probability of Harris winning the election. We use a generalized linear model (GLM) to evaluate how different factors—such as poll type, polling organization, poll score, and transparency score—impact Harris' support rate. The model is implemented using the stan_glm function, with a Gaussian distribution applied to describe the variability in support percentages.

In our analysis, we filtered the data to include only polls from organizations with a poll score above 3, ensuring the reliability of our data sources. We selected predictors including poll_type, pollster, pollscore, and transparency_score. Since the response variable (support percentage) is continuous, we utilized a Gaussian linear regression model.

The model assumes that the distribution of support percentage, given the polling characteristics, follows a normal distribution. This assumption makes the parameter estimation more straightforward and is commonly used in practice. We assigned normal priors with a mean of 0 and a variance of 2.5 for the model coefficients, which helps to maintain reasonable uncertainty while avoiding overfitting. Additionally, an exponential prior was included to handle extra variation in the model, contributing to the stability of the estimated results.

3.1 Model set-up

Define (y_i) as the predicted support percentage for Harris in the (i)-th poll. The predictor variables include (x_1, x_2, x_3, x_4, x_5, x_6), corresponding to poll type (State or National), pollster identity (e.g., Marquette Law School, Siena/NYT), poll score, transparency score, state, and pollster organization respectively. The model can be described by the following equations:

$$y_i \mid \mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{1}$$
$$\mu_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 \tag{2}$$
$$\beta_0 \sim \text{Normal}(0, 2.5) \tag{3}$$
$$\beta_j \sim \text{Normal}(0, 2.5), \quad j = 1, 2, 3, 4, 5, 6 \tag{4}$$
$$\sigma \sim \text{Exponential}(1) \tag{5}$$

The model is executed in R using the `rstanarm` package. Default priors from `rstanarm` are used, with the priors set to have a mean of zero and a moderate standard deviation to ensure a reasonable level of regularization.

3.1.1 Model justification

Considering the historical polling data and what we know about the political landscape, we believe that different aspects of polls will have a notable impact on Harris' predicted support in the upcoming election. Specifically, polls from McCourtney Institute/YouGov, YouGov/Center for Working Class Politics, higher poll scores, and greater transparency tend to have a positive influence on Harris' support. In contrast, polls from Siena/NYT, The Washington Post, YouGov, and YouGov Blue generally show a negative impact on her predicted support. Our purpose is to determine how much each polling characteristic affects voter support, thus helping us confirm or reconsider our assumptions about voter preferences.

We used a Gaussian linear regression model to examine the connection between polling characteristics and Harris' predicted support percentage. The support percentage (y_i) is a continuous measure, and its distribution aligns well with the assumptions of Gaussian regression. This method allows us to investigate how several factors—like poll type, pollster score, and transparency level—affect the level of support for Harris. By numerically encoding these predictors, we can better understand the influences on polling outcomes, ultimately offering a clearer picture of Harris' potential performance in the upcoming election.

Further justification for this model is based on its ability to demonstrate how different polling organizations and their characteristics affect Harris' predicted support percentage. The intercept value represents the baseline level of support when all other predictors are set to zero, providing a reference point. Each coefficient then reflects the expected change in support,

Table 1: Summary of the Linear Regression Model

	first_model
(Intercept)	43.387
	(4.986)
numeric_grade	1.859
	(1.624)
as.factor(methodology)Live Phone	−1.280
	(2.374)
as.factor(methodology)Mixed Voting	0.012
	(2.329)
as.factor(methodology)Online Ad	−0.948
	(2.399)
as.factor(methodology)Online Panel	−2.321
	(2.407)
as.factor(methodology)Probability Panel	−1.492
	(2.423)
duration	0.030
	(0.006)
sample_size	0.002
	(0.001)
transparency_score	−0.323
	(0.160)
stateCalifornia	−16.090
	(1.530)
stateConnecticut	−12.659
	(2.081)
stateFlorida	2.113
	(0.858)
stateGeorgia	0.021
	(0.569)
stateIowa	−0.751
	(2.097)
stateMaine	−5.214
	(1.369)
stateMaine CD-1	−7.540
	(2.173)
stateMaine CD-2	1.640
	(1.390)
stateMaryland	−17.786
	(1.612)
stateMassachusetts	−16.475

depending on factors like poll type, pollster identity, poll scores, and transparency measures. Positive coefficients, such as those for McCourtney Institute/YouGov and YouGov/Center for Working Class Politics, suggest increased support for Harris, while negative coefficients, such as those for Siena/NYT, The Washington Post, YouGov, and YouGov Blue, indicate a decrease in support.

The relatively modest R^2 value reflects that the model only captures part of the variation in Harris' support, which is not unexpected given the unpredictable nature of polling data and the complex dynamics of voter behavior. Despite this, including key polling attributes allows us to examine how different factors contribute to voter support, helping us understand the sources of variation in predicted support levels. The choice of Gaussian linear regression is appropriate in this case, as it effectively models the continuous outcome variable and provides a clear framework for interpreting the relationship between polling features and voter preferences.

4 Results

Our results are summarized in Table 2.

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

Please don't use these as sub-heading labels - change them to be what your point actually is.

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Table 2: Explanatory models of flight time based on wing width and wing length

	First model
(Intercept)	43.387
	(4.986)
numeric_grade	1.859
	(1.624)
as.factor(methodology)Live Phone	−1.280
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	(1.612)
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Appendix

A Pollster Methodology Overview and Evaluation

A.1 Overview of Siena/NYT

Siena College Research Institute (SCRI) and The New York Times launched a collaborative political poll in July 2013. Siena/NYT was known for its rigorous methodology and accuracy, which provided its first real-time midterm election poll in 2018.In 2024, FiveThirtyEight named it the most accurate pollster in the United States. The polling methodology emphasizes live phone interviews and representative sampling and focuses on transparency and statistical accuracy to provide a deep understanding of voter sentiment.

A.2 Target Population, Frame, and Sample

- Target Population: Registered voters or likely voters in the United States, especially voters in major battleground states during an election in 2024.

- Sample Frame: U.S. registered voters based on a national voter file maintained by L2, with a cell phone number that matches the voter file.

- Sample Size: Sample sizes vary across different polls. The poll in late October 2024 surveyed over 2,500 voters, and 2,097 of them completed the full survey. The margin of error for likely voters is about ± 2.2 percentage points.

A.3 Sample Recruitment

The sample was conducted by live telephone interviews in both English and Spanish. Over 98% of respondents were contacted by telephone.

A.4 Sampling Approach and Trade-offs

Siena/NYT used a stratified sampling method. Polls were stratified by demographic characteristics such as political party, race and region. This improves accuracy but adds cost and complexity. It also makes it challenging to reach certain populations such as young voters.

Advantages of stratified sampling:

- Generates a representative sample that captures the diverse opinions of different voter populations.

- Helps to ensure that under-represented groups are given appropriate weighting, and reduces potential bias.

- Provides a more accurate reflection of the wider population by stratifying on key characteristics.

Disadvantages of stratified sampling:

- Increased cost and time to complete polls, especially for live telephone interviews.

- There are challenges in reaching specific demographic groups, such as younger voters who may be less likely to participate in the poll.

- Reliance on weighting adjustments to correct for response discrepancies, which does not fully eliminate residual bias.

A.5 Non-response Handling

Non-response was a key problem for Siena/NYT. The poll used weighted adjustments for demographic characteristics such as age, race, gender, education, and different political parties to address non-response bias. The weighting adjustment was used to ensure that the sample closely matches the larger population and compensates for differences in response rates across demographic groups. However, non-response can still present residual bias even with weighting, especially when certain demographic groups have been less likely to respond to survey calls.

A.6 Questionnaire Evaluation

Strengths:

- Minimize bias through the use of straightforward and non-leading questions.

- Transparency was maintained by publishing the questions verbatim to allow for public scrutiny.

- Bilingual interviewers ensured that respondents could participate in their preferred language (English or Spanish), which increased the participation of Spanish-speaking voters and improved the quality of respondents' answers.

Weaknesses:

- The length of the poll can lead to respondent fatigue, which affects the quality of the data and increases dropout rates.

- It can be challenging to limit calls to less than 15 minutes, which can lead to incomplete or rushed responses, thus affecting the overall reliability of the data.

A.7 Conclusion

The Siena/NYT poll uses stratified sampling and live phone interviews to reach a representative sample of voters. While the use of composite weighting and bilingual interviews provides advantages such as transparency and reduced bias, challenges remain including high costs and the potential for bias due to non-response. Despite these drawbacks, Siena/NYT's commitment to transparency and rigorous methodology makes it a reliable source for understanding voter sentiment and opinion.

B Idealized Methodology and Survey

B.1 Overview

The objective of this survey is to predict voter sentiment in the upcoming U.S. presidential election, by using a budget of $100,000 to collect accurate and varied data on voting intentions, candidate favourability, and key issues from a representative sample of registered or likely voters across the United States. The methodology is designed to maximize accuracy, minimize bias and take into account a variety of demographic, geographic and political factors that influence voting behaviour.

B.2 Sampling Approach

The sampling approach is designed to increase coverage and ensure that a representative voting population is covered. This will be achieved by using a combination of stratified random sampling and quota sampling of key demographics.

B.2.1 Stratification Variables

- Age: 18-29, 30-44, 45-64, 65+

- Gender: Male and Female

- Race: White, Black /African American, Hispanic/Latino, Asian, Native and Other

- Education level: High School, Some College, Bachelor's Degree, Graduate Degree, Other

- Geographic region: Northeast, Midwest, South, West

- Political Party: Democratic, Republican, Independent, Other

B.2.2 Sample Size

The target sample size was 10,000 respondents, which are stratified by the Stratification Variables described above. This stratification ensures that all major voter groups are proportionately represented. 10,000 samples have a margin of error of about $\pm 1\%$ and a confidence level of 95%, which is appropriate for predicting elections.

B.3 Recruitment Strategy

The recruitment strategy was separated into two main approaches to ensure a diverse and representative sample:

Online Survey panels:

- Work with established survey panels such as Lucid or YouGov.

- These panels have access to large representative databases of voters.

- Recruiting through panels ensures quality and reliability, as they have built-in validation and quality control processes.

Social Media Advertising:

- Use social media platforms such as Facebook, Instagram and LinkedIn to reach potential respondents.

- Target groups that are underrepresented in traditional panels, including young voters and minority groups.

- Social media ads will be customized with demographic information to increase reach and participation.

Incentives: Offer gift card lottery prizes to all participants to encourage participation and ensure a high response rate.

B.4 Data validation and quality control

To maintain the integrity of the data, we will take the following measures:

- **Attention Checks:** At least two 'attention check' questions will be included in the survey to identify inattention or robots.

- **Duplicate Detection:** Use email or IP-based verification to prevent duplicate responses. Ensure that each respondent provides only one response set to keep the dataset unique.

- **Response Time Monitoring:** Track the time it takes respondents to complete surveys. Responses with apparently faster-than-average completion times are labelled as potentially low-quality.

- **Data Consistency Check:** Analyses the consistency of responses, especially between related questions. Inconsistent answers will be labelled for review.

- **Panel partner validation:** For respondents recruited through an online survey panel, rely on the panel provider's in-built validation systems. These systems use various quality checks, such as identity verification and response consistency, which ensure high-quality data from panel participants.

B.5 Poll aggregation and forecasting

B.5.1 Poll aggregation

- 'Poll of polls' approach: Survey data will be combined with data from some reliable polling sources such as Lucid, YouGov and others. This approach aggregates the results of multiple reputable polls to improve the forecast reliability by reducing bias and individual polling errors.

- Weighting adjustments: Polls are weighted according to sample quality, size, repeatability, and demographic match. Demographic mismatches are adjusted using raking to ensure that the aggregated data accurately represents the U.S. population.

B.5.2 Forecasting Method

- Bayesian modelling: Aggregate polling data is combined with historical electoral trends and demographic information using Bayesian statistical models. This approach allows for dynamic updating as new data becomes available, which improves accuracy.

- Uncertainty Quantification: Includes confidence intervals to express uncertainty in forecasts for a more detailed interpretation.

B.6 Budget Allocation

- Survey Panel Recruitment: $50,000

- Social Media Advertising: $50,000

- Incentives(lottery prizes): $15,000
- Data Cleaning and Validation: $5,000

- Poll Aggregation and Modeling: $10,000

B.7 Survey Implementation

The survey will be available via Google Forms to ensure broad accessibility and easy data collection. The link to the survey will be distributed via email invitations to panellists and targeted social media adverts. To ensure maximum reach and diversity, multiple channels will be used, including Facebook, Instagram, and other social media platforms.

Distribution Plan:

- **Panel invitations:** Members of established survey panels (e.g. Lucid, YouGov) will receive email invitations to participate in the survey.

- **Social media activities:** Targeted adverts will be placed on social media platforms to reach under-represented groups, especially young voters and national minority groups.

- **Follow-up reminders:** An automated reminder email will be sent to participants who have not completed the survey to maximize response rates.

- **Survey Monitoring:** Response rates will be closely monitored throughout the data collection period and sampling methods will be adjusted if certain population quotas are not reached.

- **Accessibility:** The survey will be mobile-friendly, which will allow respondents to complete the survey on any device.

B.8 Survey Structure

C Additional data details

D Model details

D.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

D.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 algo-
rithm

References

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

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/.

Ryan Best, Aaron Bycoffe. 2024. "National: President: General Election: 2024 Polls."
    FiveThirtyEight. https://projects.fivethirtyeight.com/polls/president-general/2024
    /national/.