POLITICS

Special Issue on Forecasting the 2024 US Elections

Introduction to Forecasting the 2024 US Elections

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Abstract

This Special Issue presents a wide array of election forecasting models for the 2024 US elections. Most of these models generate forecasts for the presidential, congressional or gubernatorial races. The contributions are characterized by the variety of their approaches: citizen forecasting, electronic markets, large language models, machine learning, poll-based models, and regression analysis. In this introduction, we first summarize some of the lessons and challenges of election forecasting. We then provide a brief context of the 2024 campaign and a short overview of the articles included in the Special Issue. The forecasts point to a tight presidential race. The two-party popular vote predictions are nearly evenly split, with some favoring Trump and others Harris. However, among the models that offer an Electoral College forecast, three predict Harris will win, while five predict that Trump will return to the presidency.

The Special Issue

In April 2023, *PS: Political Science & Politics* announced the call for papers for the Special Issue on "Forecasting the 2024 US Elections." To reach as many scholars as possible, the call was advertised through related groups of the American Political Science Association and promoted on social media. Of the 26 papers that were submitted, a few were desk rejected, and the others went through the double-blind peer review process. Forty-three reviewers volunteered their time and expertise to referee one or more submissions with tight turnaround times. Based on these reviews and the authors' revisions, 18 articles were ultimately accepted. The careful critiques and suggestions offered by reviewers, the receptive incorporation of reviewer feedback by the contributors, and the steady guidance and behind-the-scenes work of the *PS* editorial team demonstrate the deep commitment to advancing the field of election forecasting.

Each election presents unique circumstances that pose challenges for forecasters, and this year is no different. As we discuss in more detail below, President Joe Biden's announcement on July 21, 2024, that he was dropping out of the presidential race and endorsing Vice President Kamala Harris as the Democratic nominee, upended the dynamics of the campaign. Biden's announcement also disrupted the Special Issue—it came just four days after the July 17 manuscript submission deadline. Forecasters had estimated their prediction models with an incumbent president running for a second term, and the text of their articles focused on the contest between former President Donald J. Trump and Biden. Thus, if their manuscript received a "revise and resubmit" decision, authors were given the opportunity to update their models and manuscripts to take into account Biden's decision to withdraw from the race.

In what follows, we provide an overview of US election forecasting models to help place this year's forecasts into the literature. We then move on to discuss the 2024 election and the events that pose challenges for forecasters, before summarizing the articles in this Special Issue. The 12 articles offering

This is a "preproof" accepted article for *PS: Political Science & Politics*. This version may be subject to change during the production process.

DOI: 10.1017/S1049096524001008

presidential election forecasts are presented in Table 1. The three forecasts for the US House elections and the two forecasts for the US Senate elections appear in Table 2. The forecasts show how tight the presidential race is. The two-party popular vote predictions are nearly evenly split, with some favoring Trump and others Harris. However, among the models that offer an Electoral College forecast, three predict Harris will win, while five predict that Trump will return to the presidency.

Election Forecasting

The history of election forecasting certainly has deep roots, but as a scientific endeavor it is a relatively new field of study. In political science, the first forecasting models based on political and economic indicators appeared between the mid-1970s and 1980s. The development of these models offered social scientists the opportunity to test and adjust theories related to voting behavior (Lewis-Beck 2005). While prediction as an end in itself has merits, what gives it its full relevance is the reflexive process that it generates: forecasting requires the establishment of a theoretical framework that can be generalized to all electoral contests in a given time and space. As mentioned by Rosenstone (1983, 5), "[t]he answer [about who will win] is not nearly as important as what the answering process leads us to think about." Prediction thus has scientific relevance only insofar as it improves our understanding of the factors that influence voting and political behavior more generally (Lewis-Beck and Tien 1996). Since 1994, special issues and symposia have been devoted to US election forecasting, first in the *Political Methodologist* and the *American Politics Quarterly* and, since 2001, in *PS: Political Science & Politics*. These have been prime outlets not only to make forecasts available to a wider audience, but also to showcase methodological advancements and discuss broader issues in the field.

US election forecasting models have long revolved around two main factors: the evolution of the economy and the popularity of the incumbent president. Many of the models featured in this Special Issue fit within this tradition. The economic indicators used may vary, but they generally share four characteristics: (1) they are objective indicators rather than subjective assessments from voters, (2) these measures are based on retrospective rather than prospective theories of economic voting, (3) they concern the state of the national economy rather than the personal finances of citizens, and (4) they are more often relative (observing growth or decline compared to a previous period) than "static." In addition to the economy and popularity, some authors have also incorporated measures of governmental longevity and incumbency to account for the cost of ruling and the benefits that accompany the presence of a president eligible for re-election. The dependent variable in most American models is the share of the two-party vote received by the presidential party or its candidate. However, a growing number of models now offer Electoral College forecasts as popular vote winners do not always succeed in winning the presidency.

Generally speaking, what do forecasting models tell us about American elections, and more specifically, presidential races? What have we learned from existing work? First, according to Mayer (2004), the negative impact of the time spent in office on a party's chances of re-election is one of the main lessons from the forecasting literature. While citizens may be lenient—"cut some slack" to use Mayer's terms—after four years of the same administration, when two full terms have passed, the electorate tends to be much less forgiving. The widespread acceptance of the concept of "time for change" now embraced by many forecasters, is largely attributable to its prominent use in Abramowitz's (1988) first forecasting model.

The retrospective nature of voting is another important lesson: most models suggest that voters primarily care about the government's record rather than what the future holds for them. This record encompasses not only the state of the national economy but also all facets of domestic and foreign policy (racial tensions, corruption, immigration, the conduct of war, the management of terrorism, etc.), the evaluation of which is typically measured through the president's approval rating. Some authors have challenged this view, noting that voters also look to the future when casting their ballot (Lewis-Beck 1988; Lewis-Beck and Tien 1996; Lockerbie 1991; Michelitch et al. 2012).

Regarding the nature of economic voting, we can emphasize two elements: the first, which we have already mentioned, is that it is the direction of the economy (t compared to $t – 1$) that matters, not its level at time *t*. The second element concerns the time horizon over which the state of the economy is evaluated: this usually does not exceed one year. In other words, voters tend to have relatively short memories. Therefore, what happens at the beginning of a term is not very significant. Rather, it is the *recent* evolution of the economy that captures their attention (Healy and Lenz 2014; Lewis-Beck and Stegmaier 2014). Nonetheless, there is also strong evidence that voters in the US and elsewhere consider changes in economic conditions or governmental performance over a longer time horizon than is usually assumed (see, e.g., Aytaç 2021; Stiers et al. 2020; Wlezien 2015).

Many models also rely on polling information. While the use of voting intention polls teaches us little about voters' motivations, it has at least helped clarify the "rhythm" of presidential campaigns. The work of authors like Campbell and Wink (1990) or more recently Campbell (2016) and Holbrook (2016) shows that polls become effective tools for gauging voter sentiment only around Labor Day, after which their accuracy tends to stagnate. The Democratic and Republican conventions during the summer also appear to significantly contribute to establishing the candidates' strength (Mayer 2014).

While models based on fundamental variables and polling information are still prominent, other approaches have developed in parallel, in some cases taking advantage of the emergence of new technologies. Modern-day electronic election markets first appeared in the late 1980s (Burgman 2016; see also Forsythe et al. 1992). Betting markets are founded on the premise that financial incentives should enhance accuracy-seeking behaviors. When placing bets on the potential fate of political parties or candidates, traders in these markets seek to predict how citizens will vote on election day. The market prices resulting from traders' investments are believed to reflect the collective judgement of participants about the likelihood of different outcomes. Other researchers argue that a sufficiently large and diverse group or ordinary citizens could forecast election outcomes better than most existing methods (Huber and Tucker 2024; Mongrain et al. 2024; Murr and Lewis-Beck 2021). This is largely based on the idea that errors in individual judgements cancel out in the aggregate. Furthermore, it has been suggested that delegating and/or weighting forecasts according to individual competence or sophistication could increase accuracy. Finally, researchers have recently started harnessing the power of artificial intelligence and automated sentiment analysis to detect trends in support using big data gleaned from online searches or social media and news content (see, e.g., Behnert et al. 2024; Burnap et al. 2016; Gayo-Avello 2013; Rizk et al. 2023). The increasing diversity of forecasting approaches have also prompted some researchers to combine different methods (Cuzán et al. 2005; Graefe 2023; Lock and Gelman 2010; Rothschild 2015).

The effect of the campaign on voter behavior has barely been addressed in the forecasting literature. However, this does not mean that forecasters consider campaigns insignificant. Campaigns provide voters with the necessary information (among other things, about the record of the past administration) to cast a vote that aligns with the expectations set by models. As voters acquire the information disseminated by parties and the media, their behavior becomes more predictable, thus conforming to the theoretical foundations of forecasting equations. Ultimately, one could say that the success of a campaign depends primarily on conditions independent of it, such as the state of the economy, the popularity of leaders, the conduct of a war, and so on (Holbrook 1996; see also Hillygus 2010). After all, political parties and candidates largely campaign on pre-existing conditions and must carry with them a record that can be as much a liability as an asset.

A Challenging Task

Forecasting social events, such as election outcomes, is a difficult task. There is a clear tension between the imperative of explanation (the *x*'s of a model) and that of prediction (the *y*): simultaneously fulfilling these two objectives is no small challenge. According to Campbell (2000, 182), who draws a clear boundary between explanation and prediction, it may even be unwise to embark on such an endeavor. According to him, "[t]here is no reason to forecast with one hand tied behind your back in a mistaken belief that a good forecasting model must also be a good explanatory model." Thus, forecasters should not hesitate to include factors that are conceptually difficult to dissociate from the behavior they seek to predict (and thus of little theoretical interest) if doing so allows them to achieve a higher level of accuracy.

Undoubtedly, those primarily seeking the highest level of accuracy should not be bogged down by complex theoretical refinements if rudimentary measures allow them to estimate election outcomes to the nearest tenth. Campbell nonetheless argues that explanatory research and predictive research have the potential to enrich each other. Similarly, Dubin (1969) argued that, although prediction and understanding are two distinct objectives of the social sciences, they should not be considered incompatible. We believe the contributions in this Special Issue have seek to avoid what Dubin (1969, 14) calls the "paradox of precision," which is to "achieve precision in prediction without any knowledge of how the predicted outcome was produced."

It should also be noted that data collection raises a number of issues: first, although a variable may be theoretically interesting, if no rigorous measurements have been collected over the years (and over a sufficiently long period of time), it cannot be integrated into a model. Therefore, it is not surprising that several predictive models include only a small number of cases. Moreover, for a model to be genuinely predictive, the data must be available *before* the election takes place—the lead time of a prediction is a fundamental in assessing the overall quality of a model (Lewis-Beck 2005). This effectively eliminates any information made public (or collected) after the election. Thus, the theoretical framework can be severely constrained by the incompleteness of the databases available to researchers. It is therefore not surprising that economic variables occupy a significant place in the realm of election forecasting: a high number of economic indicators of all kinds have been recorded on a monthly, quarterly, or annual basis by state and non-state institutions for several decades, which is not the case for most attitudinal and social variables, the collection of which is often sporadic or too recent to be of any utility in developing a predictive model (Lewis-Beck and Rice 1992). We concur with Linzer (2014) when he writes that "[f]undamentals-based election forecasting is running into the limits of what additional theory is going to contribute. The greatest impediment to the development of better election forecasting models is not a lack of theory; it is a lack of data." The articles in this collection show how some of the challenges inherent to forecasting elections can be overcome or addressed.

The 2024 US Elections

A number of former US presidents have sought to regain their old office in the White House following defeat either by seeking once again the nomination of their party or by running as third-party candidates. However, only Grover Cleveland was successful in serving nonconsecutive terms in office. More than a century later, former president Trump is trying to repeat Cleveland's feat. While the 2024 election was supposed to be a rematch between Donald Trump and incumbent president Joe Biden, Biden's decision to drop out of the race and endorse his vice-president, Kamala Harris, for the Democratic nomination unexpectedly changed the dynamic of the election. Biden made his decision amidst concerns over his age and cognitive ability, announcing it just three days *after* the Republican Convention and less than a month *before* the Democratic Convention.

The 2024 election has a historical significance for another reason. Kamala Harris is only the second woman in American history to clinch a major political party's presidential nomination. If elected, she would not only become the first woman, but also the first Black woman and first person of Indian descent, to occupy the highest office in the United States. However, the historical meaning of her candidacy has not been central to the Democratic campaign. It seems like Harris has deliberatively chosen to avoid "identity politics" (Daniels 2024; Keith 2024). Recent studies, focusing specifically on Kamala Harris as the Democratic vice-presidential nominee, have shown how identity cues could both positively and negatively affect her political fate (see, e.g., Clayton et al. 2023; Knuckey and Mathews 2024).

On many accounts, the 2024 campaign has been a humbling experience for election forecasters. The campaign has been punctuated by a series of unpredictable events which have, or could have, completely altered the outcome of the November elections—Trump's assassination attempt days before his nomination, Biden's withdrawal from the race, or Robert F. Kennedy Jr's decision to suspend his presidential bid and endorse Trump are prime examples of events defying political prediction. Nonetheless, unpredictable events are often considered as "noise" that should do little to hinder election outcomes from reflecting the more fundamental determinants of political support. Others would argue that the inclusion of polling information, especially when updated throughout the campaign, can guard against the risk of ignoring meaningful developments.

Presidential, Congressional, and Gubernatorial Forecasting Models and Approaches

This year's Special Issue includes a mix of national-level and state-level models employing various methodologies and approaches to predict the outcome of the presidential, congressional and gubernatorial races. To summarize the predictions of this year's models, we present separate tables for the presidential forecasts (Table 1) and congressional forecasts (Table 2). Figure 1 shows the (unweighted) average national two-party vote share and Electoral College forecasts from all models. Figure 2 shows average two-party vote share forecasts per state from state-level models included in the Special Issue and the corresponding Electoral College prediction. Collectively, the forecasts in the current Special Issue point toward a scenario somewhat reminiscent of the 2016 election: a majority of the Electoral College for Donald Trump without a popular vote victory.

Using national-level data, **Algara, Gomez, Headington, Liu and Nigri** argue that presidential approval and the popularity of the incumbent party's partisan brand (which they measure as the incumbent party's standing on the congressional generic ballot) are two distinct concepts that can both be mobilized to predict the outcome of presidential and congressional elections. **Gruca and Rietz** use traders' expectations from the Iowa Electronic Markets (IEM) to predict the vote shares of major party candidates. In such markets, participants invest real money by buying and selling contracts related to candidates or parties according to their anticipated performance. The value of each competitor's share can then be converted into a vote projection. Prediction markets such as the IEM combine both an incentive system whose primary goal is to ensure the sincerity and quality of the information revealed by participants, as well as an information aggregation mechanism. In principle, the market should also respond immediately (or at least fairly quickly) to changes in the informational environment of the participants.

Table 1. US Presidential Election Forecasts, 2024

Forecasters	Model Name	Predicted Winner		Predicted Outcome for Kamala Harris		Level
		2P-PV	EC	2P-PV	EC	
Algara, Gomez, Headington, Liu and Nigri	Presidential Approval and Party Brands	Trump	Trump	47.2	168	National
Gruca and Rietz	Iowa Electronic Markets	Harris	–	54.5	–	National
Lockerbie	Prospective	Trump	–	49.1	–	National
Saeki	Partisan-Bounded Economic	Harris	Harris	52.4	318	National
Tien and Lewis-Beck	Political Economy	Trump	–	48.1	–	National
DeSart	Long-Range State-Level	Harris	Trump	50.7	256	State
Enns, Colner, Kumar and Lagodny	State Presidential Approval/State Economy	Trump	Trump	49.7	226	State
Lindsay and Allen	Dynamic	Harris	Harris	*	289	State
Mongrain, Nadeau, Jérôme and Jérôme	State-by-State Political Economy	–	Trump	–	197	State
Cerina and Duch	PoSSUM Poll	Harris	Trump	50.4**	237	National and State
Thompson, Cadieux, Ouellet and Dufresne	Citizen Forecasting	Trump	–	45.0***	–	National and State
Graefe	PollyVote	Harris	Harris	50.8	276	NA

Notes. 2P-PV = two-party popular vote (%). EC = Electoral College. *Lindsay and Allen predict Harris will win the popular vote by a 3.8-percentage point margin. **As of September 1st, Cerina and Duch's popular vote forecast is 47.6% for Harris and 46.8% for Trump. We computed the two-party vote share for Harris using these numbers. Note that Cerina and Duch intend on publishing a final vote share forecast prior to election day. **Thompson, Cadieux, Ouellet and Dufresne collected expectations data among their respondents before Biden's decision to withdraw from the presidential race. Their forecast only applies to Joe Biden.

Table 2. US House and Senate Election Forecasts, 2024

Forecasters	Model Name	House Forecast for Democrats		Senate Forecast for Democrats	
		Seats	Control	Seats	Control
Algara, Gomez, Headington, Liu and Nigri	Presidential Approval and Party Brands	222	(D)	51	(D)
Lockerbie	Prospective	211*	(R)	–	–
Quinlan and Lewis-Beck	Political History	215	(R)	46	(R)

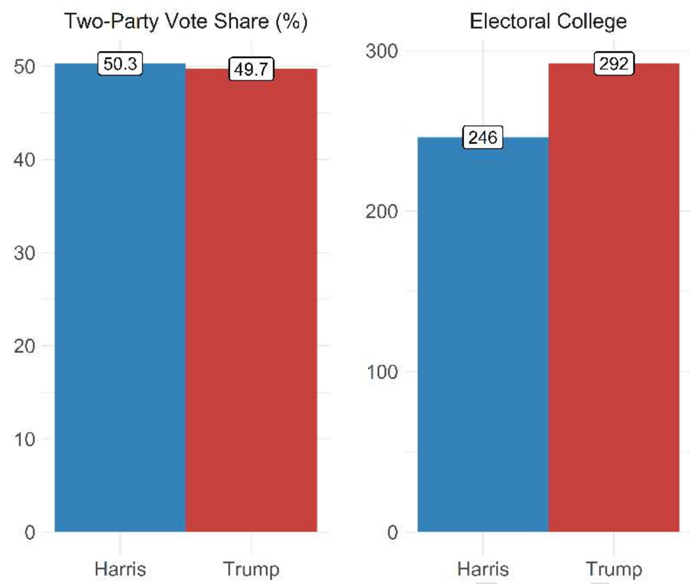
Notes. (D) = Democratic. (R) = Republican. *More specifically, Lockerbie predicts a loss of 12 seats for the Democrats.

Lockerbie suggests using individuals' prospective evaluation of their own financial situation a year from now (i.e., the extent of economic pessimism among voters) to predict both the vote share of the incumbent party's presidential candidate and change in the number of seats in the US House of Representatives for the incumbent presidential party. **Saeki** introduces a Partisan-Bounded Economic Model based on economic growth, presidential popularity, and shifts in party identification within the electorate to predict the incumbent's vote share and Electoral College outcome. Importantly, Saeki suggests truncating outlier values for economic growth, as these values contribute to weaken the association between macroeconomic conditions and election results. **Tien and Lewis-Beck**'s Political Economy Model has been around, under somewhat different forms, since the 1980s. One could say that the Political Economy Model represents the core of most structural forecasting models as it relies solely on presidential approval and economic growth to predict the incumbent's vote share. In the pure tradition of retrospective voting, this model portrays the electoral act as a referendum on the state of the national economy and the work done by the president during his time in office. **Thompson, Cadieux, Ouellet and Dufresne** leverage the "wisdom of crowds" principle by using the electoral expectations of ordinary citizens. Survey respondents across the United States were asked to assign winning probabilities to Donald Trump, Joe Biden and Robert F. Kennedy Jr. at the national and state levels. These probabilities were then transformed into vote share forecasts at the national level and in in seven key swing states. Although Biden and Kennedy withdrew from the race, Thompson et al. provide avenues of reflection for how to conduct citizen forecasting in future research. To forecast House and Senate elections, **Quinlan and Lewis-Beck** use a model that is devoid of any public opinion or macroeconomic measures: instead the performance of the Democrats in US Congressional elections is assumed to be influenced by the degree to which the Democratic Party controls the federal government, its number of state governorships, the strength of the Republican Party in a given state, holdover seats and retirements in the Senate, and historical political shifts or "critical junctures."

Five of the presidential forecasting models in this Special Issue provide state-level predictions of the two-party popular vote in every state and the District of Columbia. We can then have a forecast of which candidate will in in each state, including swing states (Arizona, Georgia, Michigan, Nevada, North Carolina, Pennsylvania and Wisconsin), as well as a projection of the Electoral College outcome. Although popular vote winners usually go on to win the presidency, there is no guarantee that getting most votes nationally will translate to an Electoral College majority as evidenced by the 2000 and 2016 elections. The first of these models, **DeSart**'s Long-Range State-Level Model, which is based on prior election results, polling information, the number of consecutive terms spent in office by the incumbent party, and the home state advantage of candidates, produces forecasts a year ahead of the election, long before the nominees of both major parties are known. This feature proved particularly relevant in light of Biden's unexpected decision to drop out of the race. The second state-level model, **Enns, Colner, Kumar and Lagodny**'s State Presidential Approval/State Economy Model, circumvents the limitations related to finding state-level data over multiple election cycles by using a multilevel regression with poststratification modelling (MrP) approach to estimate state-level public opinion from national surveys. This model relies on fundamental variables, namely macroeconomic conditions and presidential approval, as well as previous election results and the home state advantage of presidential and vice-presidential candidates. The third state-level model, by **Lindsay and Allen**, is characterized by its parsimony as it includes only two variables, namely the previous margin of victory in a given state and the average of current polls in that state. The authors calibrated their model at six different points in time between mid-April and election day, showing that as election day nears, more weight is gradually given by their model to horserace polling compared to previous election results. Finally, the fourth state-level model, **Mongrain, Nadeau, Jérôme and Jérôme**'s State-by-State Political Economy Model includes a wide array of variables measured at the state level capturing previous election results, presidential approval, historical partisan patterns, electoral strongholds for the major parties, change in unemployment over the incumbent's term in office, and the challenger's performance in primaries. Apart from Lindsay and Allen, who predict a close Electoral College victory for Kamala Harris, the other state-level models hint at a second Trump presidency. **Cerina and Duch** offer an AI election polling approach, which they describe as a protocol for surveying social-media users with multimodal large language models (PoSSUM). In a nutshell, this approach provides an analysis of digital traces or online content gathered from US 𝕏 (formerly Twitter) accounts in order to infer political preferences and opinions—likely vote choice in the present case. Cerina and Duch also employ MrP to obtain state-level vote share forecasts.

Graefe's PollyVote combines results from various prediction methods, including econometric models, voting indices, vote intention and expectation polls, election markets, and expert judgement. It is, in essence, a forecast of forecasts. The 2024 PollyVote forecasts integrated, along with the predictions of other models and approaches, the presidential forecasts included in this Special Issue. Combining methodologies has been argued to increase accuracy and reduce the bias associated with omitted information. It also prevents individuals from "cherry-picking" models based on flawed or motivated reasoning.

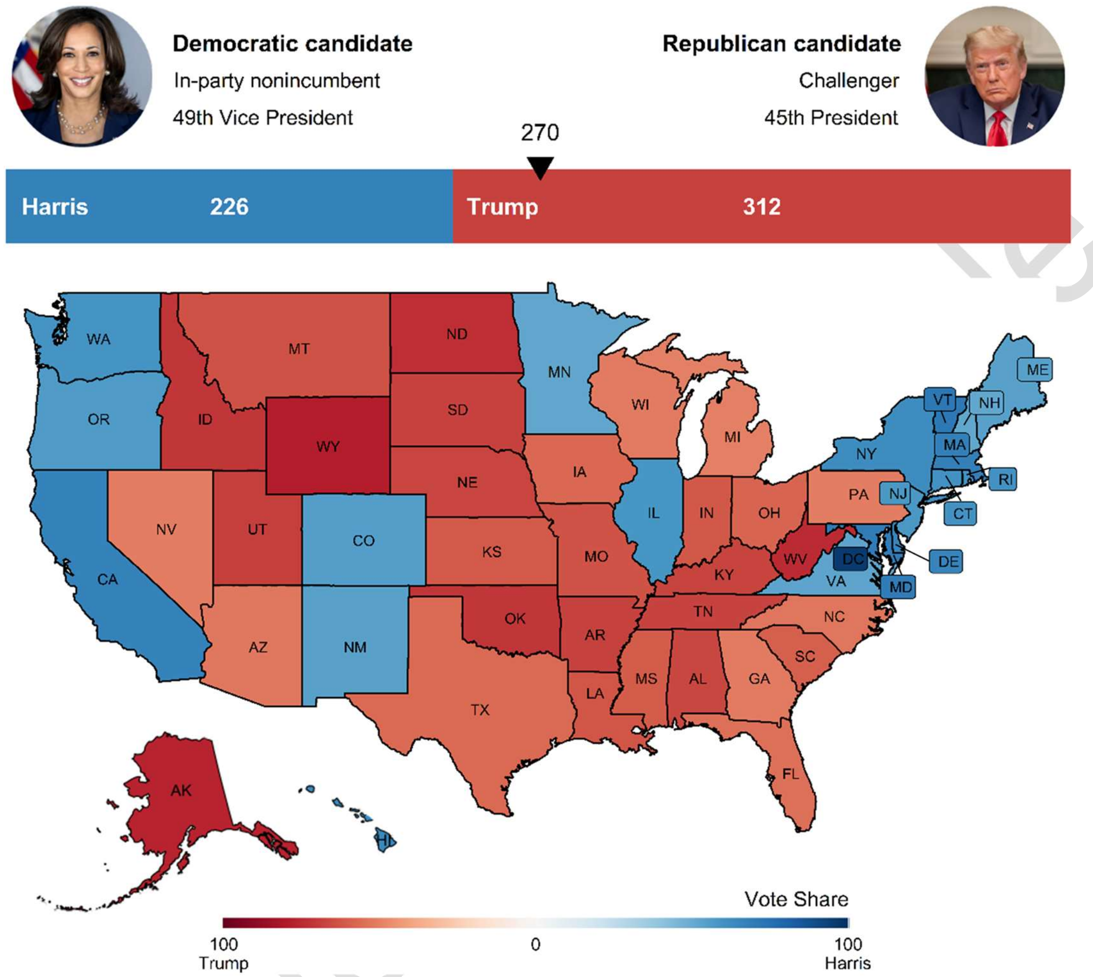
Figure 1. Average Two-Party Vote Share and Electoral College Forecasts



Notes. Average forecasts from all presidential models (see Table 1) with the exception of Thompson, Cadieux, Ouellet and Dufresne, who explicitly provided a forecast for Joe Biden. For the Electoral College, forecasts were rounded to the nearest integer.

Despite the important policymaking power of state legislatures and governors, the US forecasting literature has mostly focused on presidential and, to a lesser extent, congressional elections. In recent years, only a few scholars have provided forecasts for state elections (e.g., Hummel and Rothschild 2014; Klarner 2018). **Love, Carlin and Singer** thus make a much-needed contribution by proposing a machine-learning approach to predict the outcome of the 11 gubernatorial elections taking place in 2024. More precisely, this approach consists in the use of a LASSO regression, a type of linear regression that uses shrinkage in order to select variables and avoid overfitting.

Figure 2. Average State-Level Vote Share Forecasts, State-Level Models Only



Notes. Average two-party vote share forecasts per state computed using the state-level estimates produced by Cerina and Duch; DeSart; Enns, Colner, Kumar and Lagodny; Lindsay and Allen; Mongrain, Nadeau, Jérôme and Jérôme.

Other Forecasts, Advances, and Considerations

In addition to predicting election results, there are other election-related forecasts that our Special Issue contributors offer. Much political science research has examined the determinants of voter turnout, yet **Bednarczuk** is the first to provide predictive models of US voter turnout. His national-level model relies solely on past turnout rates and projects a 2024 presidential turnout rate of 65.3%. The state-level model includes lagged turnout and incorporates institutional and demographic measures—specifically same-day voter registration, percentage of the population that is white, and the percentage with a college degree. Compared to 2020, in 2024, 41 states are expected to have higher turnout rates.

Building on their earlier research predicting party primaries, **Dowdle, Adkins, Sebold and Steger** generate forecasts for the 2024 Republican nomination. The models weigh pre-primary factors (polls, finances, and endorsements) and the results of the Iowa caucuses and New Hampshire primaries and correctly pointed to Trump's nomination. As a former president running for his party's nomination, Trump had advantages similar to an incumbent—media attention, campaign funds, and a cadre of loyal supporters.

While most election forecasters either focus on macro-level structural factors or survey aggregation, **Catamarri** makes the case for election prediction based on individual-level voting behavior theory. Using logistic regression approaches (standard and Bayesian), Camatarri tests predictive models on American National Election Studies (ANES) data from 2012, 2016 and 2020 and includes economic and political evaluations, ideology and socioeconomic status variables. This survey-based and theoretically-appealing approach is an area ripe for future research.

Finally, **Sediqe** draws our attention to the importance of minority groups that mobilize around a pressing policy issue, and who could sway election results, especially in swing states. Her study focuses on Michigan, which is home to nearly 250,000 American Muslim registered voters, many of whom have been directly impacted by the humanitarian crisis in Gaza. Their disapproval of President Biden's foreign policy has resulted in a dramatic decline in Democratic Party support in Michigan among Muslim voters. Finding ways in state-level models to include substantial shifts in minority group support could help forecasters improve the accuracy of forecasts, and ensure our models reflect salient policy concerns.

Conclusion

As Campbell and Mann (1996, 27) noted regarding American presidential elections, "[t]he pattern of media coverage […], which chronicles every unforeseen event and strategic choice by the candidates and their handlers and analyzes every blip of reaction in public opinion, reinforces the impression that each election is in flux and wildly unpredictable." This observation likely applies to the majority of democratic regimes where the media and analysts often prolong the suspense until the results are revealed. Nevertheless, forecasters are not fortune tellers. Election forecasting is indeed a complex alchemy. Anyone seeking the perfect predictive equation will be quite disappointed. One cannot expect the combination of a few carefully selected variables to predict election outcomes without fail. Every now and then, models will be wrong. But we learn as much from inaccurate forecasts as we do from accurate ones. Forecasting models are a powerful tool to "field test" theories about electoral behavior. They have also recently become an equally powerful tool to infer collective behavior from the enormous amounts of information generated by our digital lives. The 2024 US election has the potential to be rich in lessons for election forecasters and, by extension, to the political science community. The articles included in this Special Issue tackle important theoretical and methodological questions—How can we use national-level data to produce state-level estimates? How should we measure economic performance? Is there wisdom in the crowd? Do financial incentives enhance accuracy? Do the digital traces we leave behind tell us something about the broader political landscape? How important is minority voting to understand election outcomes? And many more questions. In the end, we believe one should recognize that the forecasting process is more important than the forecast itself.

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