Introduction to Forecasting the 2024 US Elections

Philippe Mongrain, *University of Antwerp*
Mary Stegmaier, *University of Missouri*

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, and 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. This introduction first summarizes 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 almost evenly split, with some favoring Donald Trump and others Kamala Harris. However, among the models that offer an Electoral College forecast, three predict that Harris will win and five predict that Trump will return to the presidency.

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; the remainder 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 ultimately were 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 presidential election presents unique circumstances that pose challenges for forecasters, and this year was no different. As we discuss in more detail, 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 only 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 President Joe 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.

This article provides an overview of US election forecasting models to help place this year's forecasts into the literature. We then discuss the 2024 election and the events that pose challenges for forecasters, followed by a summary of the articles in this Special Issue. The 12 articles that offer 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 almost evenly split, with some favoring Trump and others Harris. However, among the models that provide an Electoral College forecast, three predict that Harris will win and five predict that Trump will return to the presidency.

Corresponding author: Philippe Mongrain *is a postdoctoral researcher at the University of Antwerp in the Media, Movement and Politics research group. He can be reached at philippe.mongrain@uantwerpen.be.*
Mary Stegmaier *is vice provost for international programs and professor of government and public affairs at the University of Missouri. She can be reached at stegmaierm@missouri.edu.*

doi:10.1017/S1049096524001008

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 1, Cerina and Duch's popular-vote forecast was 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 to publish 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 applies only 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.

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 the 1980s. The development of these models gave social scientists the opportunity to test and adjust theories related to voting behavior (Lewis-Beck 2005). Although 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 *Political Methodologist* and *American Politics Quarterly* and, since 2001, in *PS: Political Science & Politics*. These journals are 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 align with 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" (i.e., observing growth or decline compared to a previous period) than "static." In addition to the economy and popularity, some authors also incorporate 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 reelection. 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 because 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 reelection is one of the main lessons from the forecasting literature. Whereas 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 a second 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 (e.g., racial tensions, corruption, immigration, the conduct of war, and the management of terrorism), the evaluation of which typically is 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 emphasize two elements. The first, which was mentioned previously, 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 also is strong evidence that voters in the United States and elsewhere consider changes in economic conditions and governmental performance over a longer time horizon than usually is assumed (Aytaç 2021; Stiers, Dassonneville, and Lewis-Beck 2020; Wlezien 2015).

Many models also rely on polling information. Although the use of voting-intention polls teaches us little about voters' motivations, it at least has helped to clarify the "rhythm" of presidential campaigns. The work of authors such as Campbell and Wink (1990) and, 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 contribute significantly to establishing the candidates' strength (Mayer 2014).

Whereas 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 judgment of participants about the likelihood of different outcomes. Other researchers argue that a sufficiently large and diverse group of 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 based largely on the idea that errors in individual judgment 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 (Murr 2015). Finally, researchers recently have begun to harness the power of artificial intelligence (AI) and automated sentiment analysis to detect trends in support using "big data" gleaned from online searches and social media and news content (Behnert, Lajic, and Bauer 2024; Burnap et al. 2016; Ceron, Curini, and Iacus 2016; Gayo-Avello 2013; Rizk et al. 2023). The increasing diversity of forecasting approaches also have prompted some researchers to combine different methods (Cuzán, Armstrong, and Jones, Jr. 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, we could state 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 preexisting 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 (i.e., the *x*'s of a model) and that of prediction (i.e., the *y*): simultaneously fulfilling these two objectives is no small challenge. According to Campbell (2000), who drew a clear boundary between explanation and prediction, it even may be unwise to embark on such an endeavor. According to Campbell (2000, 182), "[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 who are primarily seeking the highest level of accuracy should not be hindered by complex theoretical refinements if rudimentary measures allow them to estimate election outcomes to the nearest tenth. Campbell (2000) nonetheless argued that explanatory research and predictive research have the potential to enrich one another. 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 that the contributions in this Special Issue seek to avoid what Dubin (1969, 14) called 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 two 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. Second, for a model to be genuinely predictive, the data must be available *before* the election takes place—the lead time of a prediction is crucial for 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 therefore is not surprising that economic variables occupy a significant place in the realm of election forecasting. A high number of economic indicators of all types have been recorded on a monthly, quarterly, or annual basis by state and non-state institutions for several decades. This is not the case for most attitudinal and social variables, the collection of which often is 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 wrote 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 Special Issue 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 previous office in the White House following defeat either by seeking once again the nomination of their party or by running as a third-party candidate. However, only Grover Cleveland was successful in serving nonconsecutive terms in office. More than a century later, former President Donald Trump is trying to repeat Cleveland's feat. The 2024 election was supposed to be a rematch between Donald Trump and incumbent president Joe Biden. However, 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 amid concerns over his age and cognitive ability, announcing it only three days *after* the Republican Convention and less than a month *before* the Democratic Convention.

The 2024 election has 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 become not only 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 and Messerly 2024; Keith 2024). Recent studies that focus specifically on Kamala Harris as the Democratic vice-presidential nominee have shown how identity cues could affect her political fate both positively and negatively (Clayton, Crabtree, and Horiuchi 2023; Knuckey and Mathews 2024).

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

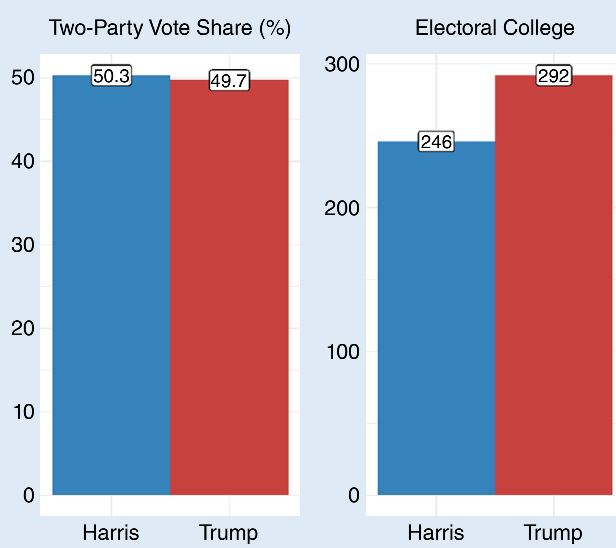
PRESIDENTIAL, CONGRESSIONAL, AND GUBERNATORIAL FORECASTING MODELS AND APPROACHES

This year's Special Issue includes a mix of national- and state-level models using 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 (see table 1) and congressional forecasts (see 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 that is somewhat reminiscent of the 2016 election: that is, a majority of the Electoral College for Donald Trump without a popular-vote victory.

Using national-level data, Carlos Algara, Lisette Gomez, Edward Headington, Hengjiang Liu, and Bianca 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 both can be mobilized to predict the outcome of presidential and congressional elections. Thomas S. Gruca and Thomas A. Rietz use traders' expectations from the Iowa Electronic Markets (IEM) to predict the vote shares of major-party

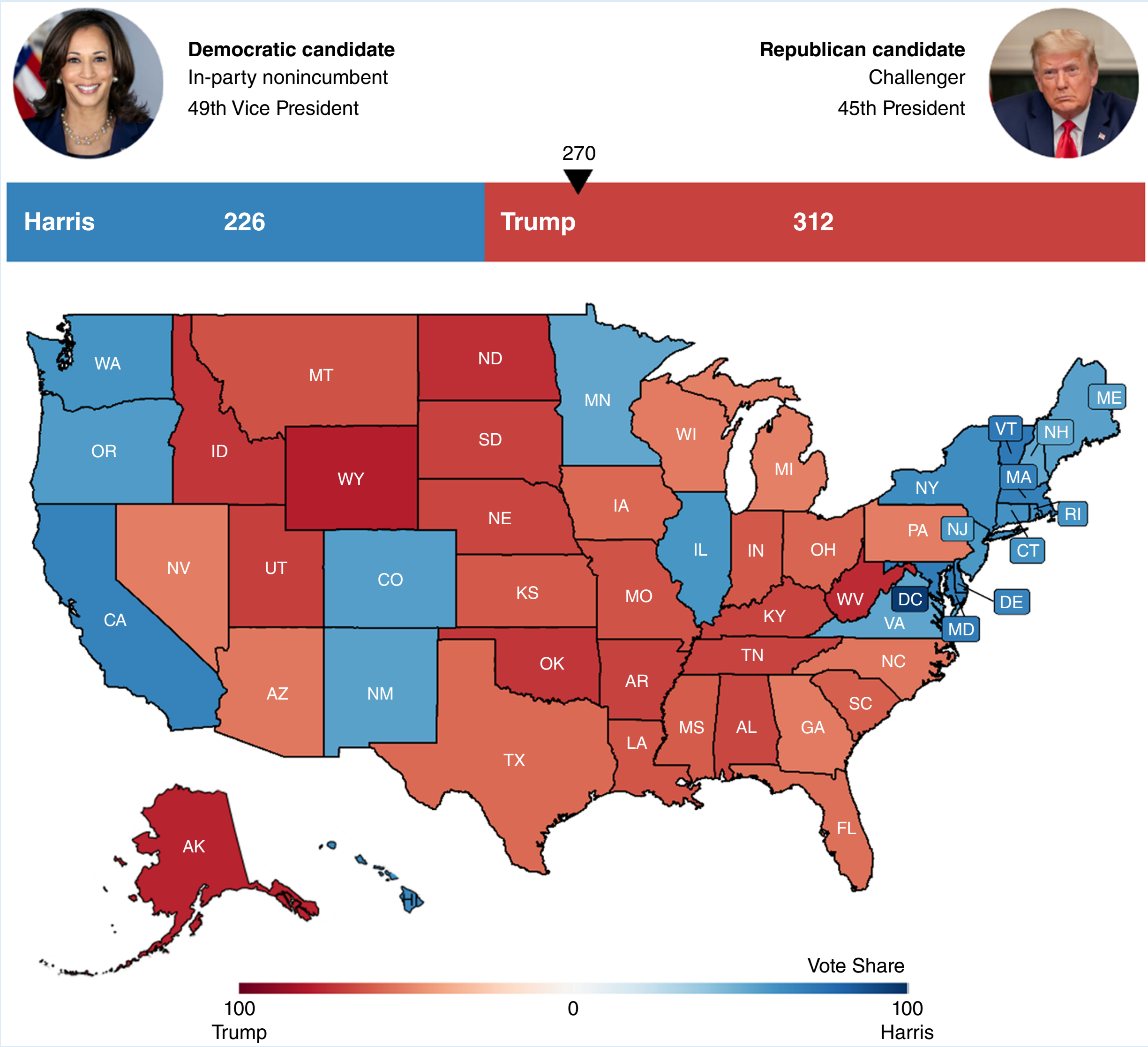
Figure 1

Average Two-Party Vote-Share and Electoral College Forecasts



Notes: Average forecasts are 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.

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



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

candidates. In these 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 then can be converted into a vote projection. Prediction markets such as the IEM combine both an incentive system, the primary goal of which is to ensure the sincerity and quality of the information revealed by participants, and an information-aggregation mechanism. In principle, the market also should respond immediately (or at least fairly quickly) to changes in the informational environment of the participants.

In his article, Brad 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 the change in the number of seats in the US House of Representatives for the incumbent presidential party. Manabu 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. Saeki importantly suggests truncating outlier values for economic growth because these values contribute to the weakening of the association between macroeconomic conditions and election results.

Charles Tien and Michael S. Lewis-Beck's Political Economy Model has been available—in somewhat different forms—since the 1980s. We could say that the Political Economy Model represents the core of most structural forecasting models because 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.

Brian Thompson-Collart, Hubert Cadieux, Catherine Ouellet, and Yannick 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 then were transformed into vote-share forecasts at the national level and in the seven key swing states. Although Biden and Kennedy withdrew from the race, Thompson-Collart et al. provide avenues of reflection for how to conduct citizen forecasting in future research.

To forecast House and Senate elections, Stephen Quinlan and Michael S. 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 then can have a forecast of which candidate will win in each state, including swing states (i.e., 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 the most votes nationally will translate to an Electoral College majority, as evidenced by the 2000 and 2016 elections. The first of these models, Jay A. 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, Peter K. Enns, Jonathan Colner, Anusha Kumar, and Julius 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 modeling (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, described by Spencer Lindsay and Levi Allen, is characterized by its parsimony because 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, demonstrating that as Election Day nears, more weight gradually is given by their model to "horse race" polling compared to previous election results. The fourth state-level model, Philippe Mongrain, Richard Nadeau, Bruno Jérôme, and Véronique 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. Finally, the fifth state-level model by Roberto Cerina and Raymond Duch offer an AI election-polling approach, which they describe as a protocol for surveying social media users with multimodal large language models (i.e., PoSSUM). Briefly, this approach provides an analysis of digital traces or online content gathered from US 𝕏 (formerly Twitter) accounts to infer political preferences and opinions—likely vote choice in this case. Cerina and Duch also use MRP to obtain state-level vote-share forecasts. Apart from Lindsay and Allen, who predict a close Electoral College victory for Kamala Harris, the other state-level models suggest a second Trump presidency.

Andreas Graefe's PollyVote combines results from various prediction methods, including econometric models, voting indices, vote-intention and vote-expectation polls, election markets, and expert judgment. In essence, it is 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. This also prevents individuals from "cherry-picking" models based on flawed or motivated reasoning.

Despite the important policy-making power of state legislatures and governors, the US forecasting literature has focused mostly on presidential and, to a lesser extent, congressional elections. In recent years, only a few scholars have provided forecasts for state elections (Hummel and Rothschild 2014; Klarner 2018). Gregory J. Love, Ryan E. Carlin, and Matthew M. 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 Least Absolute Shrinkage and Selection Operator regression, a type of linear regression that uses shrinkage to select variables and avoid overfitting.

OTHER FORECASTS, ADVANCES, AND CONSIDERATIONS

In addition to predicting election results, there are other election-related forecasts that our Special Issue authors contribute. Much political science research has examined the determinants of voter turnout, yet Michael 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, the percentage of the population that is white, and the percentage that has a college degree. Compared to 2020, 41 states are expected to have higher turnout rates in 2024.

Building on their previous research predicting party primaries, Andrew Dowdle, Randall Adkins, Karen Sebold, and Wayne Steger generate forecasts for the 2024 Republican nomination. The models weigh pre-primary factors (i.e., 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, including media attention, campaign funds, and a cadre of loyal supporters.

Whereas most election forecasters focus on either macro-level structural factors or survey aggregation, Stefano 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 data from 2012, 2016, and 2020 and includes economic and political evaluations, ideology, and socio-economic status variables. This survey-based and theoretically appealing approach is an area ready for future research.

Finally, Nura Ahmad 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 almost 250,000 American Muslim registered voters, many of whom have been impacted directly 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 to improve the accuracy of forecasts and ensure that 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 in which 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 disappointed. We cannot expect the combination of a few carefully selected variables to predict election outcomes without fail. Every now and then, models will be wrong. However, we learn as much from inaccurate forecasts as we do from accurate forecasts. Forecasting models are a powerful tool to "field test" theories about electoral behavior. They also recently have 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, 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 reveal something about the broader political landscape? How important is minority voting to understand election outcomes? Ultimately, we believe that we should recognize that the forecasting process is more important than the forecast itself. ■

REFERENCES

Abramowitz, Alan I. 1988. "An Improved Model for Predicting Presidential Election Outcomes." *PS: Political Science & Politics* 21 (4): 843–47.

Aytaç, Selim Erdem. 2021. "An Experimental Investigation of Voter Myopia in Economic Evaluations." *Electoral Studies* 74:102393.

Behnert, Jan, Dean Lajic, and Paul C. Bauer. 2024. "Can We Predict Multi-Party Elections with Google Trends Data? Evidence Across Elections, Data Windows, and Model Classes." *Journal of Big Data* 11 (30). https://doi.org/10.1186/s40537-023-00868-4.

Burgman, Mark A. 2016. *Trusting Judgements: How to Get the Best out of Experts.* Cambridge, UK: Cambridge University Press.

Burnap, Pete, Rachel Gibson, Luke Sloan, Rosalynd Southern, and Matthew Williams. 2016. "140 Characters to Victory? Using Twitter to Predict the UK 2015 General Election." *Electoral Studies* 41:230–33.

Campbell, James E. 2016. "The Trial-Heat and Seats-in-Trouble Forecasts of the 2016 Presidential and Congressional Elections." *PS: Political Science & Politics* 49 (4): 664–68.

Campbell, James E. 2000. "The Science of Forecasting Presidential Elections." In *Before the Vote: Forecasting American National Elections*, ed. James E. Campbell and James C. Garand, 169–87. Los Angeles: SAGE Publications.

Campbell, James E., and Thomas E. Mann. 1996. "Forecasting the Presidential Election: What Can We Learn from the Models?" *Brookings Review* 14 (4): 26–31.

Campbell, James E., and Kenneth A. Wink. 1990. "Trial-Heat Forecasts of the Presidential Vote." *American Politics Quarterly* 18 (3): 251–69.

Ceron, Andrea, Luigi Curini, and Stefano Maria Iacus. 2016. *Politics and Big Data: Nowcasting and Forecasting Elections with Social Media.* London: Routledge.

Clayton, Katherine, Charles Crabtree, and Yusaku Horiuchi. 2023. "Do Identity Frames Impact Support for Multiracial Candidates? The Case of Kamala Harris." *Journal of Experimental Political Science* 10 (1): 112–23.

Cuzán, Alfred J., Scott Armstrong, and Randall J. Jones, Jr. 2005. "How We Computed the PollyVote." *Foresight: The International Journal of Applied Forecasting* 1 (1): 51–52.

Daniels, Eugene, and Megan Messerly. 2024. "Harris Sidesteps the Spotlight When It Comes to Her Identity." *Politico*, August 30. www.politico.com/news/2024/08/30/harris-cnn-interview-race-gender-00176929.

Dubin, Robert. 1969. *Theory Building.* New York: The Free Press.

Forsythe, Robert, Forrest Nelson, George R. Neumann, and Jack Wright. 1992. "Anatomy of an Experimental Political Stock Market." *American Economic Review* 82 (5): 1142–61.

Gayo-Avello, Daniel. 2013. "A Meta-Analysis of State-of-the-Art Electoral Prediction from Twitter Data." *Social Science Computer Review* 31 (6): 649–79.

Graefe, Andreas. 2023. "Embrace the Differences: Revisiting the PollyVote Method of Combining Forecasts for U.S. Presidential Elections (2004 to 2020)." *International Journal of Forecasting* 39 (1): 170–77.

Healy, Andrew, and Gabriel S. Lenz. 2014. "Substituting the End for the Whole: Why Voters Respond Primarily to the Election-Year Economy." *American Journal of Political Science* 58 (1): 31–47.

Hillygus, D. Sunshine. 2010. "Campaign Effects on Vote Choice." In *The Oxford Handbook of American Elections and Political Behavior*, ed. Jan E. Leighley, 326–45. Oxford, UK: Oxford University Press.

Holbrook, Thomas M. 1996. "Reading the Political Tea Leaves: A Forecasting Model of Contemporary Presidential Elections." *American Politics Quarterly* 24 (4): 506–19.

Holbrook, Thomas M. 2016. "National Conditions, Trial-Heat Polls, and the 2016 Election." *PS: Political Science & Politics* 49 (4): 677–79.

Huber, Gregory A., and Patrick D. Tucker. 2024. "What to Expect When You're Electing: Citizen Forecasts in the 2020 Election." *Political Science Research and Methods* 12 (3): 624–32.

Hummel, Patrick, and David Rothschild. 2014. "Fundamental Models for Forecasting Elections at the State Level." *Electoral Studies* 35:123–39.

Keith, Tamara. 2024. "If Harris Wins, She Would Make History. But She Isn't Talking About That." *NPR*, September 12. www.npr.org/2024/09/13/nx-s1-5106766/kamala-harris-first-woman-racial-identity.

Klarner, Carl E. 2018. "2018 State Legislative Election Forecasts." *PS: Political Science & Politics* 51 (S1): 21–27.

Knuckey, Jonathan, and Adrienne Mathews. 2024. "Racial Resentment, Sexism, and Evaluations of Kamala Harris in the 2020 U.S. Presidential Election." *Social Science Quarterly* 105 (4): 1266–79.

Lewis-Beck, Michael S. 1988. "Economics and the American Voter: Past, Present, Future." *Political Behavior* 10:5–21.

Lewis-Beck, Michael S. 2005. "Election Forecasting: Principles and Practice." *British Journal of Politics and International Relations* 7 (2): 145–64.

Lewis-Beck, Michael S., and Tom W. Rice. 1992. *Forecasting Elections.* Washington, DC: CQ Press.

Lewis-Beck, Michael S., and Mary Stegmaier. 2014. "US Presidential Election Forecasting: Introduction." *PS: Political Science & Politics* 47 (2): 284–88.

Lewis-Beck, Michael S., and Charles Tien. 1996. "The Future in Forecasting: Prospective Presidential Models." *American Politics Quarterly* 24 (4): 468–91.

Linzer, Drew A. 2014. "The Future of Election Forecasting: More Data, Better Technology." *PS: Political Science & Politics* 47 (2): 326–28.

Lock, Kari, and Andrew Gelman. 2010. "Bayesian Combination of State Polls and Election Forecasts." *Political Analysis* 18 (3): 337–48.

Lockerbie, Brad. 1991. "Prospective Economic Voting in U.S. House Elections, 1956–88." *Legislative Studies Quarterly* 16 (2): 239–61.

Mayer, William G. 2004. "The Basic Dynamics of the Contemporary Nomination Process: An Expanded View." In *The Making of the Presidential Candidates 2004*, ed. William G. Mayer, 83–132. Lanham, MD: Rowman & Littlefield.

Mayer, William G. 2014. "What, If Anything, Have We Learned from Presidential Election Forecasting?" *PS: Political Science & Politics* 47 (2): 329–31.

Michelitch, Kristin, Marco Morales, Andrew Owen, and Joshua A. Tucker. 2012. "Looking to the Future: Prospective Economic Voting in the 2008 Presidential Elections." *Electoral Studies* 31 (4): 838–51.

Mongrain, Philippe, Nadjim Fréchet, Brian Thompson-Collart, and Yannick Dufresne. 2024. "Working the Crowd: Election Forecasting, Sophistication, and Diversity." *Canadian Journal of Political Science* (forthcoming).

Murr, Andreas E. 2015. "The Wisdom of Crowds: Applying Condorcet's Jury Theorem to Forecasting US Presidential Elections." *International Journal of Forecasting* 31 (3): 916–29.

Murr, Andreas E., and Michael S. Lewis-Beck. 2021. "Citizen Forecasting 2020: A State-by-State Experiment." *PS: Political Science & Politics* 54 (1): 91–95.

Rizk, Rodrigue, Dominick Rizk, Frederic Rizk, and Sonya Hsu. 2023. "280 Characters to the White House: Predicting 2020 U.S. Presidential Elections from Twitter Data." *Computational and Mathematical Organization Theory* 29:542–69.

Rosenstone, Steven J. 1983. *Forecasting Presidential Elections*. New Haven, CT: Yale University Press.

Rothschild, David. 2015. "Combining Forecasts for Elections: Accurate, Relevant, and Timely." *International Journal of Forecasting* 31 (3): 952–64.

Stiers, Dieter, Ruth Dassonneville, and Michael S. Lewis-Beck. 2020. "The Abiding Voter: The Lengthy Horizon of Retrospective Evaluations." *European Journal of Political Research* 59 (3): 646–68.

Wlezien, Christopher. 2015. "The Myopic Voter? The Economy and US Presidential Elections." *Electoral Studies* 39:195–204.