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Understanding Biden's Exit and the 2024 Election: The State Presidential Approval/State Economy Model

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Abstract: Our 2020 analysis correctly forecasted Biden's victory and the outcome of every state except for Georgia. That forecast relied on economic data from 125 days prior to the election and presidential approval data from 104 days (or more) before the election. Since 2000, our model would have correctly forecasted the winner in 95% of all states. We have updated our State Presidential Approval/State Economy Model for 2024. This article summarizes the model and its historical accuracy as well as new data updates. We then generate forecasts for the overall two-party popular vote, each state's outcome, and Electoral College winner for the 2024 U.S. presidential election. 100 days prior to the election, our model forecasts a split popular vote (50.3% for Trump, 49.7% for Harris), but a notable Trump advantage in the Electoral College, with just under a 3 in 4 chance Trump wins the Election. This Republican advantage 100 days prior to Election Day sheds light on Biden's abrupt decision to drop out of the race and suggests that if Harris wins, she will have overcome extremely challenging fundamentals and/or Donald Trump and the Republican Party will have squandered a sizeable Electoral College advantage.

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Using economic data from 125 days prior to the election and presidential approval data from 104 days (or more) before the election, in 2020 we correctly forecasted Biden's victory and the outcome of every state except for Georgia (Enns and Lagodny 2021a). We have updated our State Presidential Approval/State Economy Model for 2024. This article summarizes the forecast model and its historical accuracy as well as new data updates we have made. We then generate forecasts and associated uncertainty estimates for the overall two-party popular vote, the outcome in each state, and Electoral College winner for the 2024 U.S. presidential election. 100 days prior to the election, our model forecasts a split popular vote (50.3% for Trump, 49.7% for Harris), but a notable Trump Electoral College advantage, giving him just under a 3 in 4 chance at winning the presidency. This early Republican advantage sheds light on Biden's abrupt decision to drop out of the race and suggests that if Harris wins, she will have overcome extremely challenging fundamentals and/or Donald Trump and the Republican Party will have squandered a sizeable Electoral College advantage.

The State Presidential Approval/State Economy Model

A key contribution of our approach involves estimating the percent who approve of the president in *each state*. While presidential approval is a known predictor of election outcomes, even state-level forecasts have historically relied on national-level estimates of presidential approval (Jerôme and Jerôme-Speziari 2016; Hummel and Rothschild 2014). Following our earlier work (e.g., Enns and Koch 2013; Enns, Lagodny, and Schuldt 2017), we use multilevel regression with poststratification (MRP) to estimate state-level public opinion from national surveys (Gelman and Little 1997; Lax and Phillips 2009; Pacheco 2014). MRP has increasingly been used in election polling and forecasts, with a high degree of accuracy (Daley 2024, The Economist 2024, English 2023).

MRP is a three-step approach that involves estimating a multilevel model to identify the relationship between demographic categories and the probability of survey response (in this case indicating approval of the president's handling of the job of president), using these estimates to predict the probability of approval for each demographic-geographic "type" (e.g., African American females, age 30-44, with some college education, in Texas), and then using census data to poststratify (i.e., weight) the responses to match state population values. Poststratification data come from the census and the American Community Survey (see Appendix 1 for a detailed overview of the poststratification data). Our original MRP model included age (18-29, 30-44, 45-64, 65+), education (no high school degree, high school degree, some college, college graduate (or more)), race (white, black, other) and sex (male, female) as well as an indicator for each survey, state, and region (Northeast, Midwest, South, West, or DC). Given the increasing importance of Latino voters in U.S. presidential elections (Abrajano and Alvarez 2010; Fraga, Velez, and West 2024; García Ríos, Ocampo, Reny, and Wilcox-Archuleta 2017), we have added an indicator of whether or not respondents are Hispanic to the MRP model.[1]

We were also able to obtain additional historical data from the Roper Center for Public Opinion Research and ICPSR, adding 12 additional historical surveys. Our forecast now includes individual-level data from 89 surveys conducted in June and July of election years with 111,178 total respondents (see Appendix 4 for detailed survey information). The average annual sample size is 9,265 with a minimum of 5,326 in 1988 and a maximum of 14,230 in 1992.

After using MRP to estimate the percent in each state who approve of the president, we multiplied the approval rating by −1 when the incumbent was a Republican because we code vote share as the percent of the vote going to the Democratic candidate (out of the two-party vote). This step ensures that higher values for the incumbent president always correspond with more support for the Democratic candidate. We follow Hummel and Rothschild's (2014) strategy for national-level approval and subtract a constant from the approval ratings. Hummel and Rothschild subtract a constant so that when approval equals zero, it is roughly equivalent to having no incumbent advantage. We identify the constant value based on the value that maximizes model fit for the years prior to the election being forecasted.

Presidential election outcomes also reflect economic conditions. We use the Federal Reserve Bank of Philadelphia's monthly State Coincident Indexes to measure economic conditions in *each state*. These data begin in January 1979; therefore, 1980 is the first election included in the analysis. This index uses four separate economic components: "nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and the sum of wages and salaries with proprietors' income (two components of personal income) deflated by the consumer price index (U.S. city average)" to measure current economic conditions in each state.[2] Although *leading* economic indicators might be preferable to *coincident* indicators for election forecasts (Erikson and Wlezien 2008; Erikson and Wlezien 2020), state leading indicators are not available after February 2020 because the Philadelphia Fed suspended release of these data due to measurement complications from the COVID-19 pandemic. Similar to Erikson and Wlezien (2016), we calculate the average monthly percent change in coincident indicators through June of the election year, weighting months closer to the election more heavily. This weight means that economic shifts closer to the election influence the measure more, based on evidence that voters place more emphasis on recent economic changes than economic changes at the start of the presidential administration (Erikson and Wlezien 2008). We select the specific weight based on the weight parameter that best fits the data in previous elections. See Appendix 2 for a detailed discussion of the weight parameter and coincident economic indicator measurement.

To capture historical voting patterns, the model includes each state's deviation from the national vote in the past election (Campbell, Ali, and Jalalzai 2006; Hummel and Rothschild 2014). To account for the boost candidates tend to get in their home state, we code the state of the Democratic candidate 1, the state of the Republican candidate −1, and all other states 0. If both candidates are from the same state, such as Hillary Clinton and Donald Trump in 2016, all values are a zero.[3] The model also includes the lagged value of the presidential candidates' home state. We expect this coefficient to be negative because it accounts for the return to typical voting levels in that state in the subsequent election (Hummel & Rothschild 2014, Berry & Bickers 2012). Candidates also tend to get a boost in the home state of the vice-presidential candidates, so we include a variable indicating home state of the vice presidential candidates coded the same way. The lagged value of vice presidential candidate home state variable is not significant, perhaps because the magnitude of the boost is smaller, so we do not include the lag of this variable in the model.

Similar to Hummel & Rothschild (2014), to control for the influence of popular third-party candidates, we include the percent of votes obtained in each state the election *after* they ran. We include third party candidates four years after they ran to account for their impact on the estimated influence of each state's deviation from the national vote in the past election in the model. If the third-party candidate had a differential influence across the states in the prior election, this influence would affect the lagged value of each state's deviation from the national vote. By including the percent of votes received by third-party candidates in the prior election, the overall estimate for state deviation from the national vote is purged from the third-party effect, making this variable a more consistent predictor of vote outcomes. Because John Anderson's state vote share was correlated with two-party vote share (which we confirm with a likelihood ratio test), controlling for Anderson's vote share in each state in 1984 ensures that our estimated relationship between lagged two-party vote share deviation and current two-party vote share is not biased. Consistent with Hummel & Rothschild (2014), despite Perot's impressive vote share in 1992, the percent of votes he received in each state did not appear to influence two-party vote share ($p=0.22$), so we do not include Perot's 1992 vote share in 1996. We do find evidence that Perot's 1996 vote share improves model fit, so we do include the 1996 vote share in the 2000 model. Again, by including vote share in the *subsequent* election, we are only including information available before the fact in our forecasts.

For 2024, We made three updates to our approach. Our forecast now accounts for the unique Electoral College vote allocation in Maine and Nebraska. These states allocate two electoral votes to the state popular vote winner and one electoral vote based on the presidential vote in each congressional district (two districts in Maine and three in Nebraska). To estimate the Electoral College vote in these districts, we calculate the difference between each congressional district's 2020 presidential vote and the state-wide vote. We then take the 2024 state-wide forecast and adjust each district by the same amount of difference as in 2020. For example, in 2020 Biden received 40.2% of the two-party vote in Nebraska and 53.3% of the two-party vote in Nebraska's District 2 (a difference of 13.1%). Our 2024 forecast for District 2 in Nebraska takes our 2024 state-wide forecast and adds 13.1%. We do this for each district in Nebraska and Maine. This approach assumes that the difference between district vote and state vote has not changed. While an imperfect assumption, it is a much better assumption than assuming each district has the same vote as the overall state. In practice, the five Electoral College votes from these districts have not influenced election outcomes, but our updated approach offers a more accurate representation of the Electoral College process.

Vice President Harris's entrance as the Democratic presidential candidate raises the question of whether our measure of incumbent presidential approval will be less successful than if Biden had remained in the race.[4] The 1988 and 2000 elections, when Vice President George Bush and Vice President Al Gore were the incumbent party candidates, suggest a clear answer. These elections were our model's second and third least accurate forecasts (1992, when Ross Perot obtained 19 percent of the vote as a third-party candidate, is our least successful forecast). To evaluate whether different approval ratings of Bush and Gore influence our forecast accuracy, we measured the difference between net approval of the president and vice president during June and July in these election years; i.e., (% approve of the president - % disapprove) – (% approve of the vice president - % disapprove). We then adjusted the presidential approval measure in each state by this amount. Data limitations necessitate this blunt approach, but shifting our estimate of incumbent presidential approval based on whether the current vice president is more or less popular than the president has several desirable properties. First, because we are comparing evaluations of the incumbent president and vice president asked in the same way in the same surveys, responses are directly comparable. Second, since we are evaluating differences in net approval ratings, results are not influenced by don't know or unsure responses, which might be higher for the vice president given less public visibility. Finally, because both individuals were in the current presidential administration, differences in approval likely reflect meaningful differences in evaluations of the individuals. If responses to these questions reflect evaluations of the overall presidency or party, we would not expect the public to evaluate the president and vice president differently.

At a minimum, this measure offers a directional signal of whether just using presidential approval without an adjustment would over or under-estimate the Vice President's electoral fortunes. We thus have a clear decision criterion for whether to incorporate this adjustment into the model. If our 1988 and 2000 forecasts improve, we should use the same approach to adjust for differences between approval of Harris and Biden in 2024. If the forecasts do not improve, we should not. This adjustment decreases our one-step-ahead (i.e., before-the-fact) forecast error in 1988 by 22 percent (missing 7 states instead of 9) and in 2000 by 40 percent (missing 6 states instead of 10). Given the substantial improvement, we follow the same approach in 2024, adding the difference between Harris and Biden approval to our estimates of state presidential approval.[5]

Our third update is the removal of a dummy variable to account for the potential unique influence of Southern states on presidential vote. Historically, even when including each state's prior vote in the model, Southern states were more likely to vote Republican.[6] However, McKee, et al. (2024) document shifting population and voting patterns in the South, suggesting this Southern effect may no longer hold. Indeed, Appendix 3 shows that in recent elections, after conditioning on individual state voting history, adding a binary indicator for Southern states no longer adds explanatory power to the model. We thus opt for a more parsimonious approach and drop the Southern state variable from our 2024 forecast model.

Historical Accuracy

Table 1 presents the estimated relationships between the variables in the State Presidential Approval/State Economy Model and the percentage of Democratic votes based on the two-party vote share in each state (and Washington, DC) from 1980 to 2020.[7] The relationships are in the expected direction, they are estimated with substantial precision, and the model fit is impressive. The Adjusted R^2 indicates the model accounts for 90 percent of the variation in state presidential vote. Ideally, forecast models are parsimonious (Lewis-Beck 2005). With eight variables, the model is more parsimonious than other state-level forecasts, which range from between 12 and 19 variables (Campbell, Ali, and Jalalzai 2006; Jérôme and Jerôme-Speziari 2016; Jérôme, Jérôme, Mongrain, and Nadeau 2021; Hummel and Rothschild 2014).

This model did remarkably well in 2020, correctly predicting Biden's Electoral College win, as well correctly forecasting the winner in 49/50 states plus Washington DC. The model also provided an accurate forecast of the overall popular vote, which was based on a state population weighted average of the forecasted state outcomes. The two-party popular vote forecast was 54.5% for Biden (just over 2 percentage points above the actual two-party outcome). As a point of comparison, the reported vote intentions in the pre-election interviews from the American National Election Study (ANES) produced an identical two-party weighted result to our forecast.[8] The identical result from the ANES is especially notable because the ANES has been referred to as "the gold standard survey for scientific research on American voting behavior" (Ko, Jackson, Osborn, and Lewis-Beck 2024) and it included 8,280 pre-election interviews from August 18 to November 2, the day before the Election.[9] While the ANES is not intended to forecast elections, it is still stunning that more than 8,000 reported vote intentions up to Election Day yielded the same outcome as our forecast based on data from more than 100 days prior to the election.

Table 1 Predicting State Presidential Vote, 1980–2020

State Deviation from the National Vote$_{t-1}$	0.82*
	(0.02)
Presidential Approval	0.33*
	(0.02)
Cumulative Coincident Economic Indicators	1.43*
	(0.27)
Presidential Candidate Home State	2.47*
	(0.81)
Presidential Candidate Home State $_{t-1}$	-3.49*
	(0.82)
Vice Presidential Candidate Home State	1.87*
	(0.74)
Anderson	-0.35*
	(0.07)
Perot	-0.60*
	(0.06)
Constant	49.38*
	(0.17)
N:	561
Adjusted R^2	0.90
Standard Error of the Estimate	3.46

Notes: *=$p<0.05$. Dependent variable is the percent Democrat of the two-party vote. All variables measured at the state level. Standard errors in parentheses. N = 11 Elections X (50 states + DC). Third-party candidate information is only included in the election *after* they ran.

Although the 2020 U.S. Presidential Election was our first forecast, it is possible to use our model to generate one-step-ahead (or "before-the-fact") forecasts for previous elections. These forecasts only use information available *prior* to the historical election, so they offer a direct assessment of what the model would have forecasted if estimated in July of that election year.[10] The 1984 one-step-ahead forecast is only based on a regression model using 1980 data and 1984 variables measured in July or earlier. The 1988 one-step-ahead forecast is based on the regression model from 1980 and 1984 with 1988 variables, and so on. 2024 estimates are based on the values in Table 1 (1980-2020) and corresponding variables in 2024, measured 100 days or more before the election.[11]

Our prior research shows that our one-step-ahead forecasts would have consistently produced more accurate state and national-level forecasts than previously published forecasts (Enns and Lagodny 2021a; Enns and Lagodny 2021b). The updated model correctly predicts the winner in 91% of all states from 1984 to 2020. The one-step-ahead mean absolute error is 3.4 percentage points. The largest error was Arkansas in 1992, when the model under-estimated Clinton support by 16 percentage points. Since 2000, our one-step-ahead forecasts correctly predict 95% of all states with a mean absolute error of 2.8 percentage points. With this context, we now turn to our 2024 forecasts.

2024 Forecast

Our 2024 presidential approval data come from two surveys we conducted with Verasight as well as a Bright Line Watch survey, two Gallup surveys, and two surveys from AP-NORC.[12] The total sample size for 2024 is 10,510 respondents. Our forecast is based on the results in Table 1. Recall that survey data were collected 100 days or more prior to the election and the economic data were collected 127 days or more prior to the election. Harris announced Tim Walz as her running mate on August 8, so the home state of the Democratic Vice Presidential candidate was only known 91 days in advance. This information only affects our forecast of Minnesota.

To estimate the popular vote winner, we forecast the two-party vote share for each state and D.C. and then calculate the state population weighted average. The model forecasts a nearly even split, with 49.7% percent for Harris and 50.3% for Trump. Of course, uncertainty exists around these estimates, suggesting that the popular vote was a statistical tie 100 days prior to the election.

To estimate the range of uncertainty around this result (and the others we report), we conduct 70,000 simulations that incorporate three types of uncertainty. First, we use Clarify (Tomz, Wittenberg and King 2003) to simulate 10,000 parameters for each variable in the model (Table 1). These simulated parameters incorporate uncertainty based on the variance of the parameter estimates and are used to generate 10,000 forecasts. In addition to this prediction error, we also need to account for uncertainty in the model. To account for this error, we generate a normally distributed variable with 10,000 observations with a mean of zero and a standard deviation equal to the root mean square error for the model. We then add this error to the 10,000 forecasts that incorporate prediction error. As a result, our simulations incorporate equation and model uncertainty. We also account for potential error in the selection of the weight parameter used to estimate the cumulative weighted average of the percent change in economic conditions. While this parameter is selected based on the value that generates the best model fit in previous elections, in 2020 we showed that due to the extreme month-to-month economic shifts due to the COVID pandemic, the forecast was sensitive to the weight parameter selected. To account for the potential influence of the weight parameter chosen, we repeat the process described above seven times, once with the selected weight parameter, three times with the next highest weight parameters, and three times with the next lowest weight parameters, leading to 70,000 simulated outcomes.[13]

Of course, it is the Electoral College that determines the winner, and here Trump holds a notable advantage. Figure 1 shows the results of the 70,000 simulations described above. The x-axis indicates the number of Electoral Votes forecasted for Harris. The y-axis indicates the proportion of simulations that forecast that Electoral College outcome, so taller bars mean that according to our model, that outcome is more likely to occur. Blue bars reflect simulations which correspond with a Harris victory. Red bars correspond with a Trump victory. The model forecasts that Trump has just under a 3 in 4 chance of winning the election (approximately 73%), leaving Harris with just above a 1 in 4 chance. An exact tie, while mathematically possible, is extremely unlikely—occurring about once in every 500 simulations.

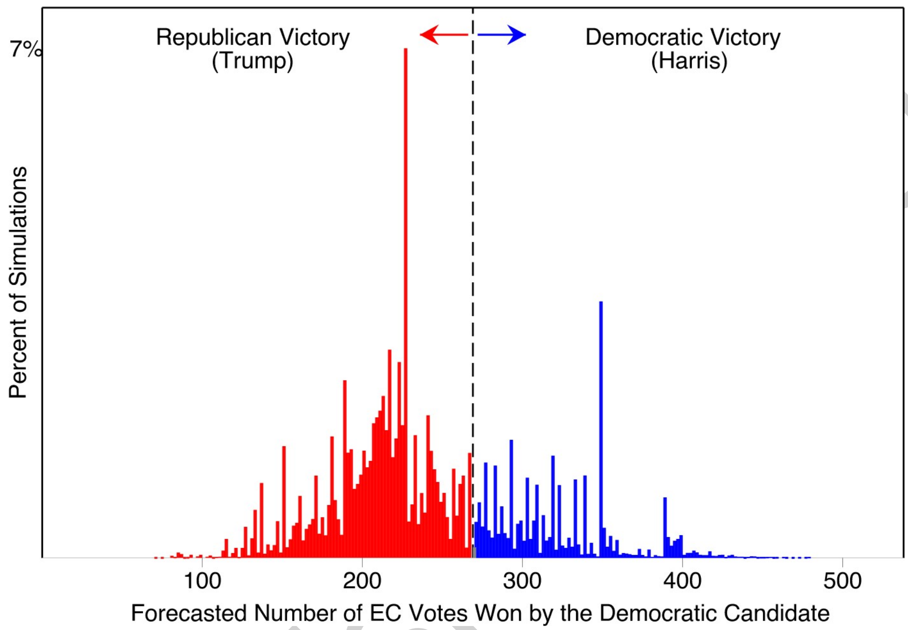

Figure 1. 2024 Electoral College Forecast Based on 70,000 Simulations Indicates that 100 Days Prior to the Election Trump Had a Notable Advantage

Figure 2 reports the percent of simulations in which Trump or Harris wins each state based on data from 100 days prior to the election. If a candidate is forecasted to win in more than 55% of simulations, we categorize the state as leaning. If more than 75% of simulations indicate a win, we categorize the state as a likely victory, and if a candidate wins in more than 98% of simulations, we label the state solid. We would consider a state which neither candidate won more than 55 percent of simulations to be a tossup, but this outcome did not occur in our forecasts. Importantly, even when a particular candidate wins more than 55 percent of simulations, the actual vote margin can be extremely close. The model forecasts 17 states to be within 5 percentage points of 50% and 10 states to be within 2.5 percentage points. Figure A-2 in the Appendix reports the specific estimate and associated uncertainty for each state.

If Trump wins all the states that currently lean in his direction, we expect he will reach 312 Electoral College votes. However, if the final 100 days of the election produce just a 2-percentage point shift in a few key states, this outcome will change. Harris should prioritize Michigan, Georgia, Pennsylvania, and Wisconsin. Our model suggests that if Trump wins two of these states, he will likely win the Election. Trump also has a path via Pennsylvania and Nevada.

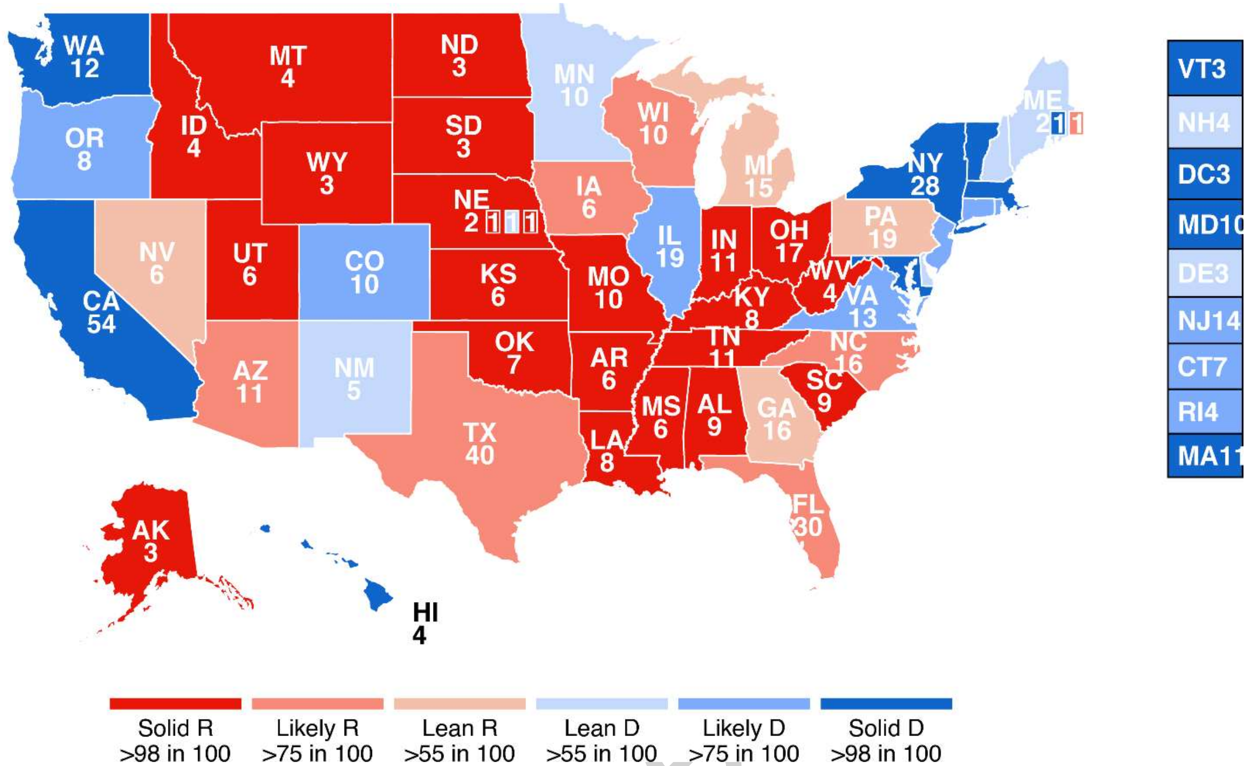

Figure 2. The Percent of Simulations in Which Trump or Harris Wins Each State based on Data from 100 Days Prior to the Election

Note: The figure reports the percent of simulations in which Trump or Harris wins each state, *not* the forecasted two-party vote share. While numerous states are forecasted to have a two-party vote share close to 50 percent, the percent of simulations where either Trump or Harris is forecasted to win always exceeds 55 percent. R corresponds with Trump, the Republican candidate. D corresponds with Harris, the Democratic candidate.

Implications for Understanding Biden's Exit the Potential Impact of Trump and Harris on the Final Outcome

On July 8, President Biden wrote to congressional Democrats, "I am firmly committed to staying in this race, to running this race to the end, and to beating Donald Trump" (Washington Post 2024). Less than two weeks later, Biden dropped out (Miller, Long, and Superville 2024). Nancy Pelosi reportedly told Biden that he could not win (Lee, Gangel, and Zeleny 2024). Our forecast indicates Pelosi was right. Given Biden's low approval ratings and economic conditions, our model forecasted less than a 1 in 10 chance of a Biden victory if he had stayed in the race. Even *after* accounting for Harris's approval ratings, which are notably higher than Biden's, the Democrats face an uphill battle.

U.S. presidential elections largely depend on the fundamentals (Gelman and King 1993), which are knowable far in advance (Enns and Richman 2013). The accuracy of past forecasts reinforces these findings. We also learn when election outcomes deviate from forecasts. The differences between expectations and outcomes highlight how campaign-specific factors can play important roles in the final outcome (Erikson 2001). The fundamentals 100 days prior to the election favor Trump. Yet, some of Trump's "closest advisers and strongest supporters are starting to worry" that he is undermining his campaign (Gorman 2024) and a number of House Republicans have critiqued the choice of JD Vance, who is historically unpopular (Rakich 2024), as a running mate (Schnell 2024). If Harris wins the election, we will not know exactly why, but we will know her victory surmounted conditions so disadvantageous to the Democratic Party that the incumbent president dropped out of the race. She will have added major momentum to the Democratic campaign and/or Trump and the Republican party will have squandered a sizeable advantage.

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DATA AVAILABILITY STATEMENT

Research documentation and data that support the findings of this study are openly available at the Harvard Dataverse at https://doi.org/10.7910/DVN/PBGFOF.

CONFLICTS OF INTEREST

The authors declare no ethical issues or conflicts of interest in this research.

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[1] Whether respondents identify as Hispanic was only consistently asked in our survey data starting in 1996, so this information cannot be included in MRP estimates prior to 1996. Appendix 1 provides additional MRP details and information on the robustness of results to alternate multilevel model specifications.
[2] Definition and data available at www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident.
[3] In 2019, Trump declared his official residence to be Florida. Given the recency of the move and Trump's long-time association with New York, our 2020 model coded his "home state" as New York. Since Trump now has a much stronger association with Mar a Lago in Florida, for 2024 we code his home state as Florida.
[4] We are grateful to the anonymous reviewers who pointed us in this direction.
[5] When there is no incumbent president or vice president in the race, such as with McCain and Obama in 2008 and Hillary Clinton and Trump in 2016, we would like to make a similar adjustment to account for potential differences between approval of the president and approval of the incumbent party's candidate. Unfortunately, this is not possible because there are no survey questions that allow a direct comparison of approval of these individuals with approval of the incumbent president.
[6] We code southern states as those in the confederacy: Alabama, Arkansas, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia.
[7] Two-party vote share, %Democratic Vote/(%Democratic Vote + %Republican Vote), is standard in election forecasts (Campbell 2016). The Republican vote share is simply the inverse of all results shown. As noted above, the 2020 forecast included an indicator for Southern states that is no longer included in our model (see Appendix 3).
[8] The 2020 ANES unweighted pre-election estimate (55.48%) and the weighted and unweighted post-election reported vote (55.99% and 57.80%, respectively), were all less accurate (Ko, Jackson, Osborn, and Lewis-Beck 2024).
[9] One pre-election interview was recorded on November 3. Ko, Jackson, Osborn, and Lewis-Beck (2024) also note that the gold standard argument for the ANES has been challenged.
[10] The one-step-ahead/before-the-fact forecast thus differs from the "jackknife" approach, which uses data from before *and* after the historical election being forecasted.
[11] In each case, the election-year variable values for each state are multiplied by the one-step-ahead coefficients and added to the constant to generate predicted values ($\hat{y}$) for each state. These predicted values represent the forecasted percent Democrat vote.
[12] Full survey details in the Appendix. The Office of Research Integrity and Assurance at Cornell University determined the human participant research protocol qualifies for exemption from IRB review (Protocol Number: IRB0148701).
[13] 2024 economic conditions are much more stable than 2020, so the seven different weight parameters produce minimal effects on the overall forecast. We nevertheless follow our 2020 approach and incorporate them into our simulated uncertainty estimates.