

An Updated Dynamic Bayesian Forecasting Model for the 2020 Election

Merlin Heidemanns*
Andrew Gelman†
G. Elliott Morris‡

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We constructed an election forecasting model for the *Economist* that builds on Linzer’s (2013) dynamic Bayesian forecasting model and provides an election day forecast by partially pooling two separate predictions: (1) a forecast based on historically relevant economic and political factors such as personal income growth, presidential approval, and incumbency; and (2) information from state and national polls during the election season. The two sources of information are combined using a time-series model for state and national opinion. Our model also accounts for some aspects of non-sampling errors in polling. The model is fit using the open-source statistics packages R and Stan (R Core Team, 2020; Stan Development Team, 2020) and is updated every day with new polls. The forecast is available at <https://projects.economist.com/us-2020-forecast/president>, a description of the model-building process is at <https://projects.economist.com/us-2020-forecast/president/how-this-works>, and all code is at <https://github.com/TheEconomist/us-potus-model>.

POLLS

We include polls at the national and state level and take each poll to be an estimate of that day’s average support for the Democratic and Republican candidates for president (ignoring respondents who express no opinion or support other candidates), with modeled bias and variance. Our goal is to estimate national and state-level trends in support for the candidates.

Modeling the public opinion time series

States are not polled every day. We share information across states contemporaneously and across time. We accomplish this by treating state level trends as correlated. We set the between-state correlation matrix by first taking the correlations of state-level election results in the past as well as other state-level predictors such as education, then setting negative correlations to zero, then adding a constant to all elements of the matrix to induce a larger between-state correlations. Thus all states will be expected to have similar trends even in the absence of frequent state-level polls, with more similar states being expected to have more

*Department of Political Science, Columbia University, New York

†Department of Statistics and Department of Political Science, Columbia University, New York

‡The Economist

similar trends. We set the details of this correlation matrix so as to get reasonable results for national and state-level swings. Across time, we use a random walk, thereby allowing the model to share information across time in a way such that the weight of other estimates decreases with their temporal distance.

$$\mu_{b,t}|\mu_{b,t-1} \sim \text{MVN}(\mu_{b,t-1}, \Sigma_b).$$

Priors on the standard deviations of the innovations in the state-level time series reflect our understanding of how much public opinion can change from day to day. We cross-validated on the 2008, 2012, and 2016 elections and the first months of 2020.

Adjustments

Poll-aggregation election forecasts performed poorly in 2016, a problem that can be attributed to polls in key midwestern states that did not appropriately adjust for nonresponse (Gelman and Azari, 2017).

We adjust for poll-specific factors including pollster house effects, polling mode (telephone or online), the population estimated by the poll (likely voters or all adults), whether it is a state or national poll, and whether it adjusts for partisanship of respondents. That last adjustment is represented by an autoregressive process to allow the party adjustment to vary over time at the national level; see Gelman et al. (2016). If a pollster does not adjust for the partisan composition of their sample, shifts in support can reflect a changing sample composition. We rely on the difference between adjusters and non-adjusters to estimate the extent to which non-adjusters are biased.

We include state and national level polling error terms, which allows for unmodeled measurement error for each poll beyond the stated margin of error (Shirani-Mehr et al., 2018). We treat state level polling error terms as correlated across states with a scaled version of the same correlation matrix we use for changes in underlying opinions across states.

FUNDAMENTALS

The fundamentals-based model combines the previous electoral outcome with economic and political factors, based on the “time for change” model of Abramowitz (2008). We predict the incumbent vote share by state in previous elections using a regularized linear model and predict the incumbent vote share in 2020 with the parameter estimates. We set the prior for μ_b on election day to the fundamentals-based prediction.

PUTTING THE PIECES TOGETHER

We combine the two forecasts by using the fundamental based prediction as the prior for election day. The random walk prior on μ_b can be visualized as going backward in time from election day to the current day of polling. Thus, the model updates the prior for the election day by the poll based forecast for the election day. Figure 1 shows the model fit for 2016. As with other forecasts, our model overrates the strength of Hillary Clinton in key midwestern

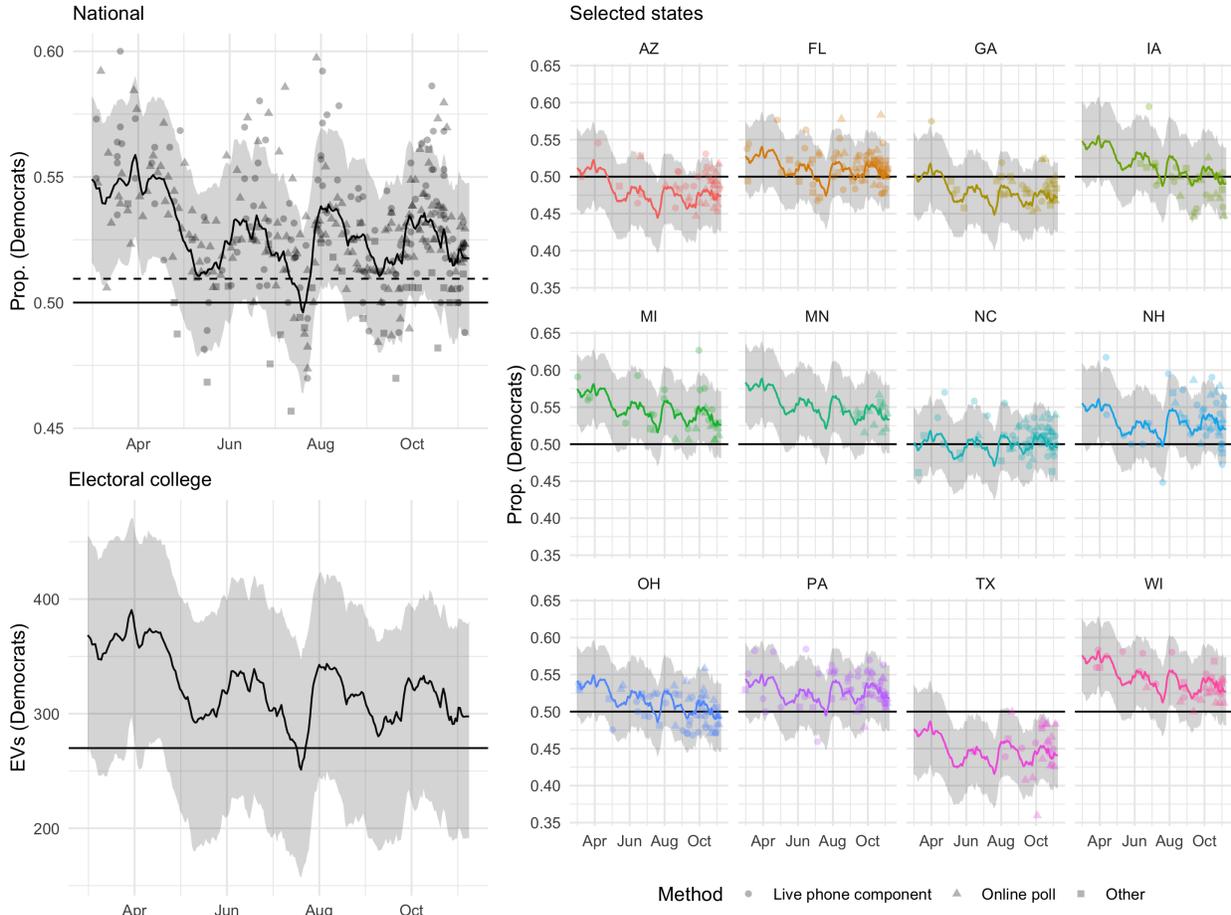


Figure 1: *Some summaries of the model, as fit retrospectively to using state and national polls from 2016. These graphs illustrate that our data and model are fitting national as well as separate state trends.*

states (see Michigan in the graph) because of failures in the state polls, but its hierarchical model with multiple error terms allows the model to avoid the overcertainty that could arise from simple poll averaging.

The current prediction for 2020 can be found on the website of the *Economist*.

CALIBRATION, UNCERTAINTY, AND WHAT IS FORECASTED

The model estimates a large number of parameters with a relatively small number of polls. Consequently, it is sensitive to our chosen prior specifications, the predictors we decide to include in our fundamentals forecast, and the construction of the covariance matrix that shares information across states. In making these choices, we want to both avoid unwarranted precision (e.g. a prediction that Biden will win Florida and with 95% probability his share is between 51% to 52%) as well as unwarranted uncertainty (e.g. Biden's share will be between 40% and 60% with 95% probability). As part of the Bayesian workflow, we started with values that we deemed reasonable a priori such as a 3% polling error for each poll based on

historical data, but also evaluated the model output to determine whether the model gave reasonable results. This only pertains to factors we were confident in modeling. Hence, we did not adjust the model for events such as a renewed COVID-19 outbreak in late-October or the death of either candidate. Finally, our model forecasts vote intentions rather than the electoral outcome. Stan allows us to propagate our uncertainty from the model’s prediction to the electoral college. Yet, we do not concern us with wide-spread vote-by-mail problems that could result in large numbers of uncounted votes.

CONCLUSION

Forecasting an election is complex and can be framed as even more so in an ‘unfamiliar’ environment. Potentially wide-spread absentee voting may change both turnout as well as the share of the population who has their voice heard. Economic shocks usually reflect negatively on the incumbent but may not if induced due to a global pandemic. Pollsters may be more actively partisan than they have been in previous elections. Overall, our model accounts for a variety of factors and treats carefully when it comes to choosing between overconfidence and expressed helplessness due to the plethora of unfamiliar events. That is, we focus on the factors we can credibly model but also believe that this election at least with respect to modeling vote intentions is not fundamentally different from the previous elections we used to calibrate it.

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