Innovations in poll aggregation and election forecasting

Leveraging more poll-level information and the fundamentals

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2020 presidential election forecast*

Right now, our model thinks **Joe Biden is very likely to beat Donald Trump** in the electoral college.

		Chance of winning the electoral college	Chance of winning the most votes	Predicted range of electoral college votes (270 to win)
	Joe Biden Democrat	around 19 in 20 or 96%	better than 19 in 20 or >99%	248-422
	Donald Trump Republican	around 1 in 20 or 4%	less than 1 in 20 or <1%	116-290

The probability of an electoral-college tie is <1%

**as of October 26 at 12:38 PM*

Our model

1. National economic + political fundamentals

2. Decompose into state-level priors

3. Polls

Uncertainty is propogated throughout the models, incorporated via MCMC sampling in step 3.

National Fundamentals

What fundamentals?

i) Index of economic growth (1940 - 2016)

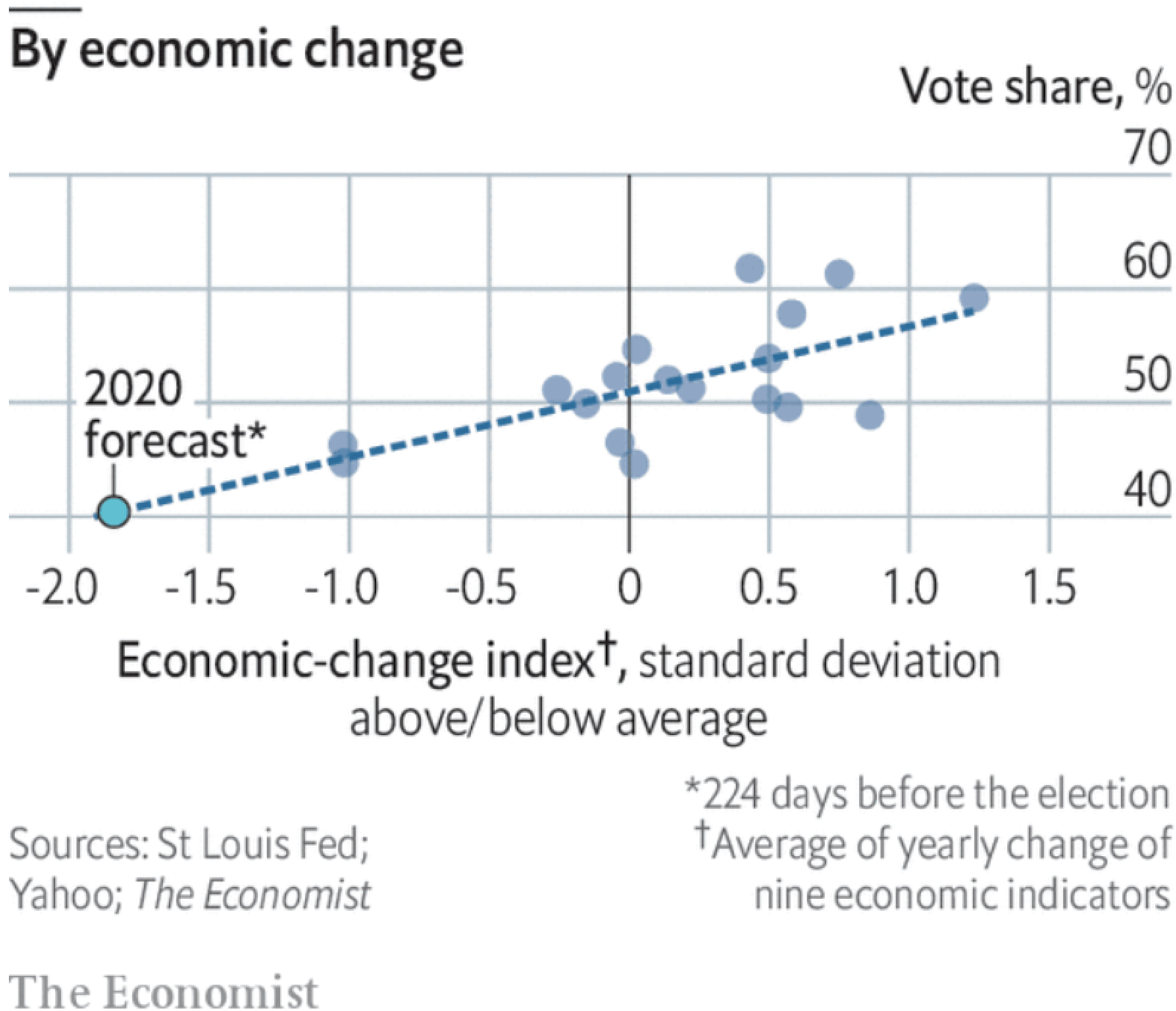
- eight different variables, scaled to measure the standard-deviation from average annual growth

ii) Presidential approval (1948 - 2016)

iii) Polarization (1948 - 2016)

- measured as the share of swing voters in the electorate, per the ANES --- and interacted with economic growth

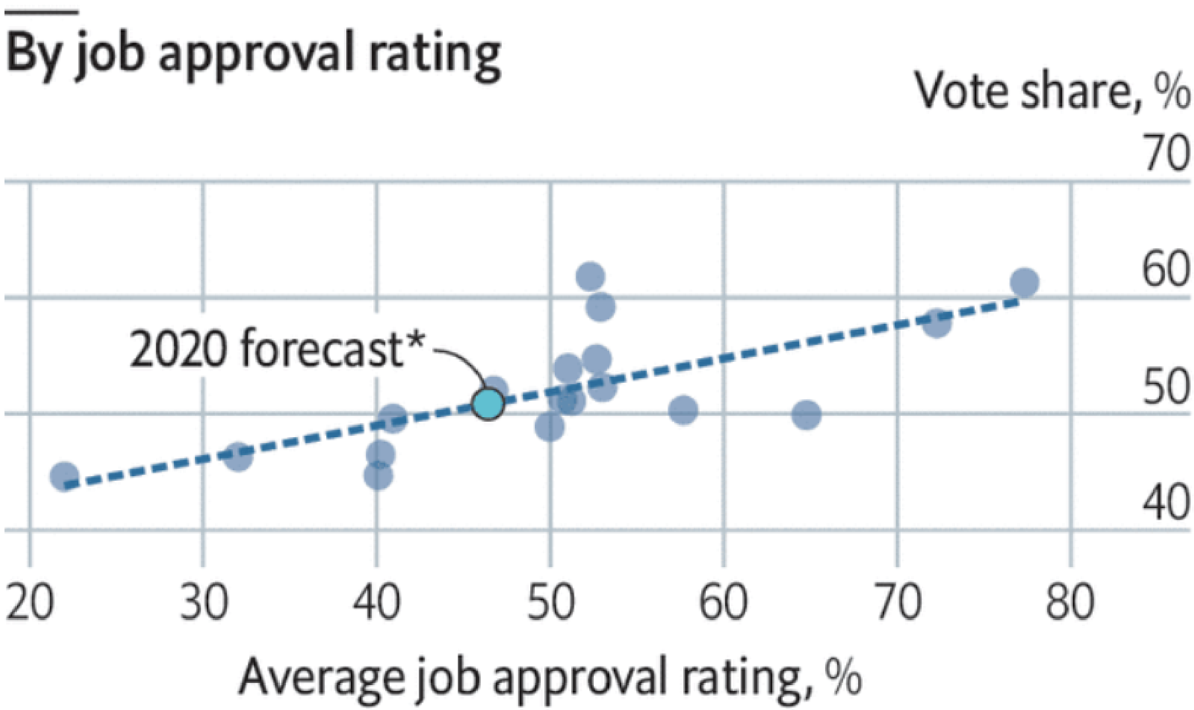
iv) Whether an incumbent is on the ballot

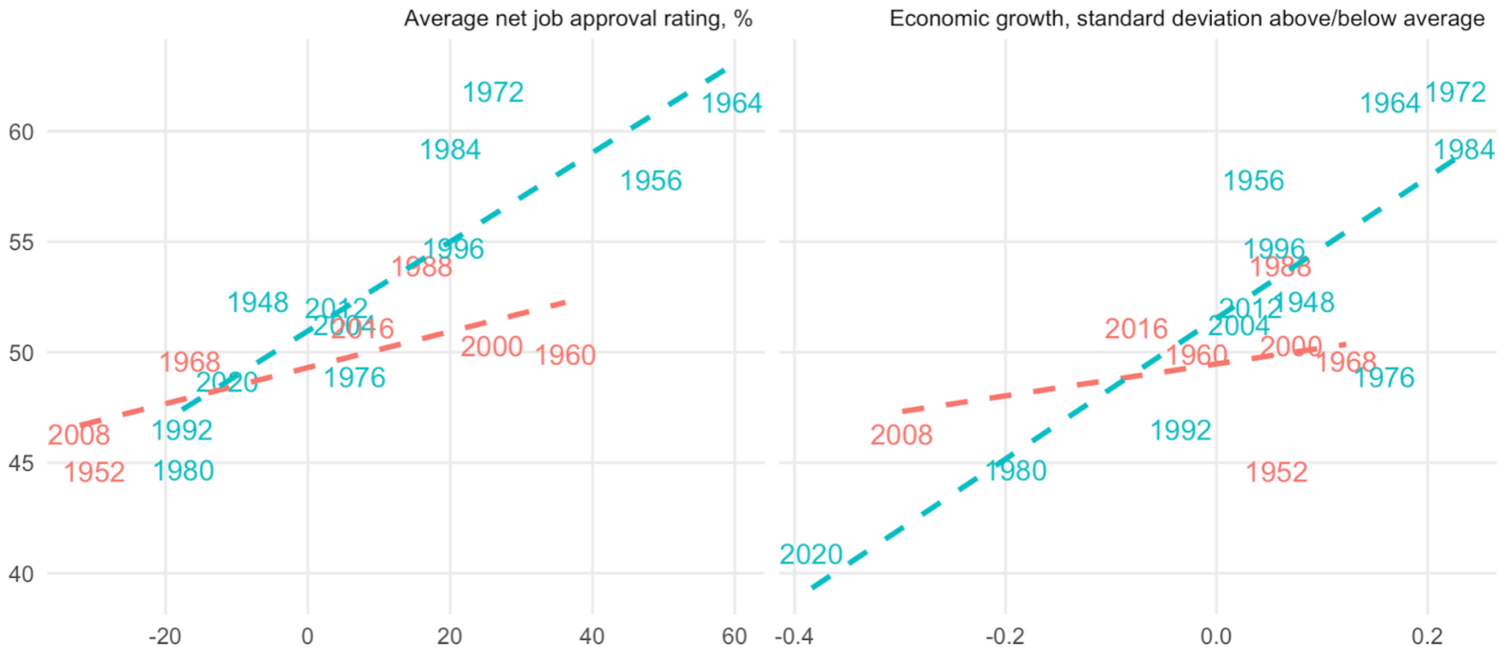

By economic change
Vote share, %
70
60
50
40
2020
forecast*
-2.0
-1.5
-1.0
-0.5
0
0.5
1.0
1.5
Economic-change index†, standard deviation above/below average
Sources: St Louis Fed; Yahoo; *The Economist*
*224 days before the election
†Average of yearly change of nine economic indicators
The Economist

Leading indicators

United States, presidential elections, incumbent party's share of the major-party vote, %

1948-2016





*Values at 41 days before the election
Sources: St Louis Fed; Yahoo; The Economist

(blue = incumbents)

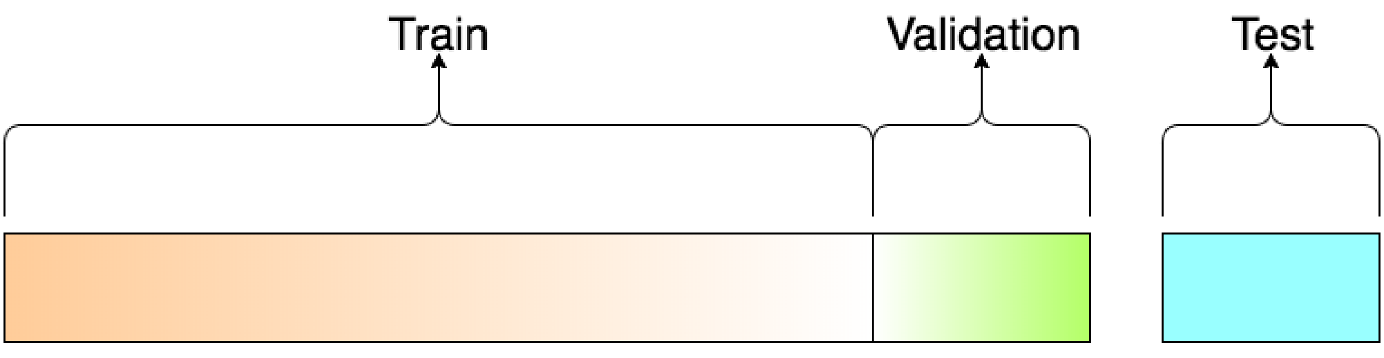
National fundamentals

Model formula:

vote ~ incumbent_running:economic growth:polarization + approval

Training

Model trained on 1948-2016 using elastic net regression with leave-one-out cross-validation



RMSE = 2.6 percentage points on two-party Democratic vote share

State-level prior

State-level prior

i) Train a model to predict the Democratic share of the vote in a state relative to the national vote, 1948-2016

- Variables are: lean in the last election, lean two elections ago, home state effects * state size, conditional on the national vote in the state

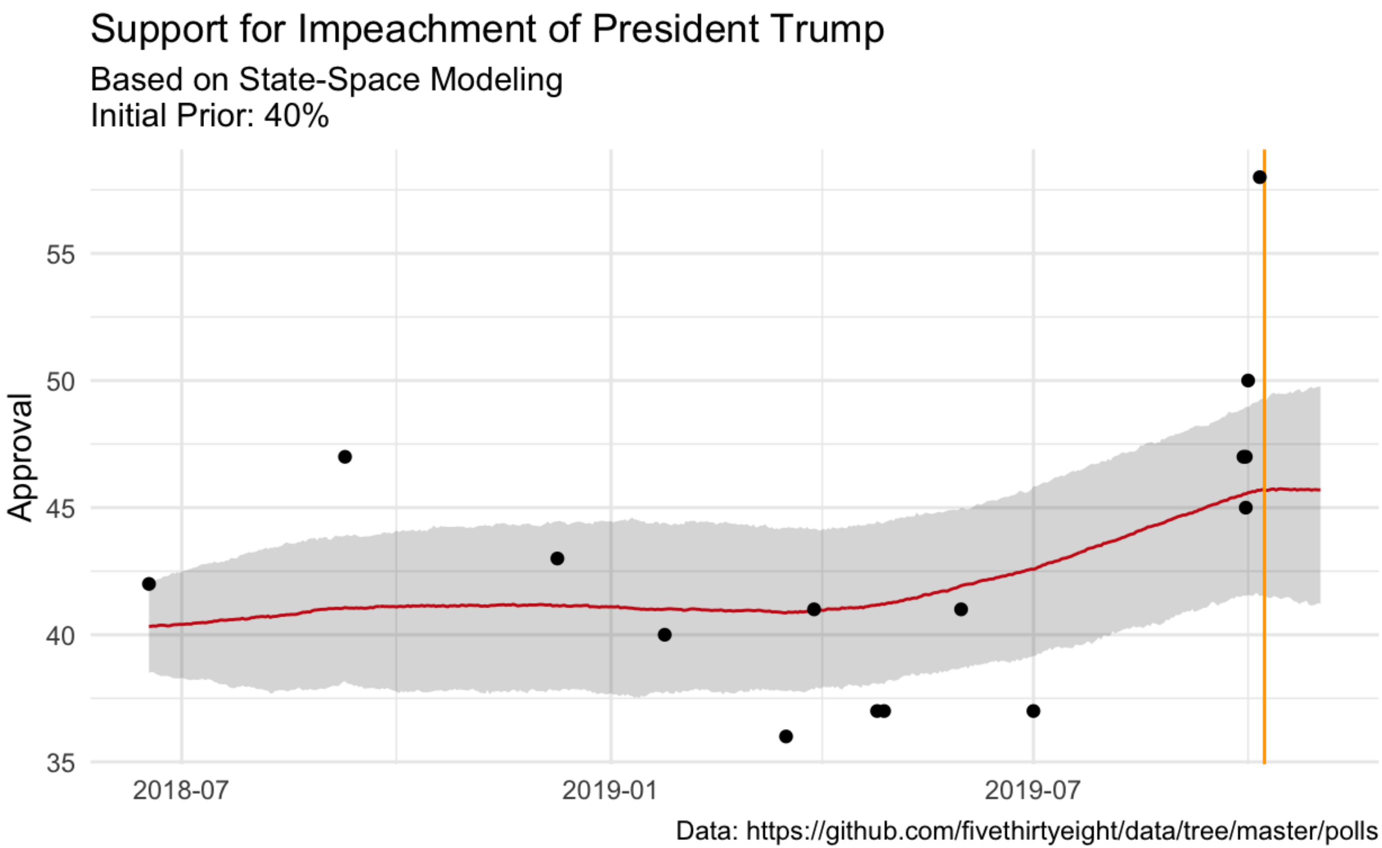
ii) Use the covariates to make predictions for 2020, *conditional on the national fundamentals prediction for every day*

ii) Simulate state-level outcomes to extract a mean and standard deviation

- Propogates uncertainty both from the LOOCV RMSE of the national model and the state-level model

Pooling the polls

It's just a trend through points...



(...but with some fancy extra stuff)

```
mu_b[:,T] = cholesky_ss_cov_mu_b_T * raw_mu_b_T + mu_b_prior;
for (i in 1:(T-1)) mu_b[:, T - i] = cholesky_ss_cov_mu_b_walk * raw_mu_b[:, T - i] + mu_b[:, T + 1 - i];
national_mu_b_average = transpose(mu_b) * state_weights;
mu_c = raw_mu_c * sigma_c;
mu_m = raw_mu_m * sigma_m;
mu_pop = raw_mu_pop * sigma_pop;
e_bias[1] = raw_e_bias[1] * sigma_e_bias;
sigma_rho = sqrt(1-square(rho_e_bias)) * sigma_e_bias;
for (t in 2:T) e_bias[t] = mu_e_bias + rho_e_bias * (e_bias[t - 1] - mu_e_bias) + raw_e_bias[t] * sigma_rho;
//*** fill pi_democrat
for (i in 1:N_state_polls){
  logit_pi_democrat_state[i] =
    mu_b[state[i], day_state[i]] +
    mu_c[poll_state[i]] +
    mu_m[poll_mode_state[i]] +
    mu_pop[poll_pop_state[i]] +
    unadjusted_state[i] * e_bias[day_state[i]] +
    raw_measure_noise_state[i] * sigma_measure_noise_state +
    polling_bias[state[i]];
}
```

Poll-level model

i. Latent state-level vote shares evolve as a random walk over time

- Pooling toward the state-level fundamentals more as we are further out from election day

ii. Polls are observations with measurement error that are debiased on the basis of:

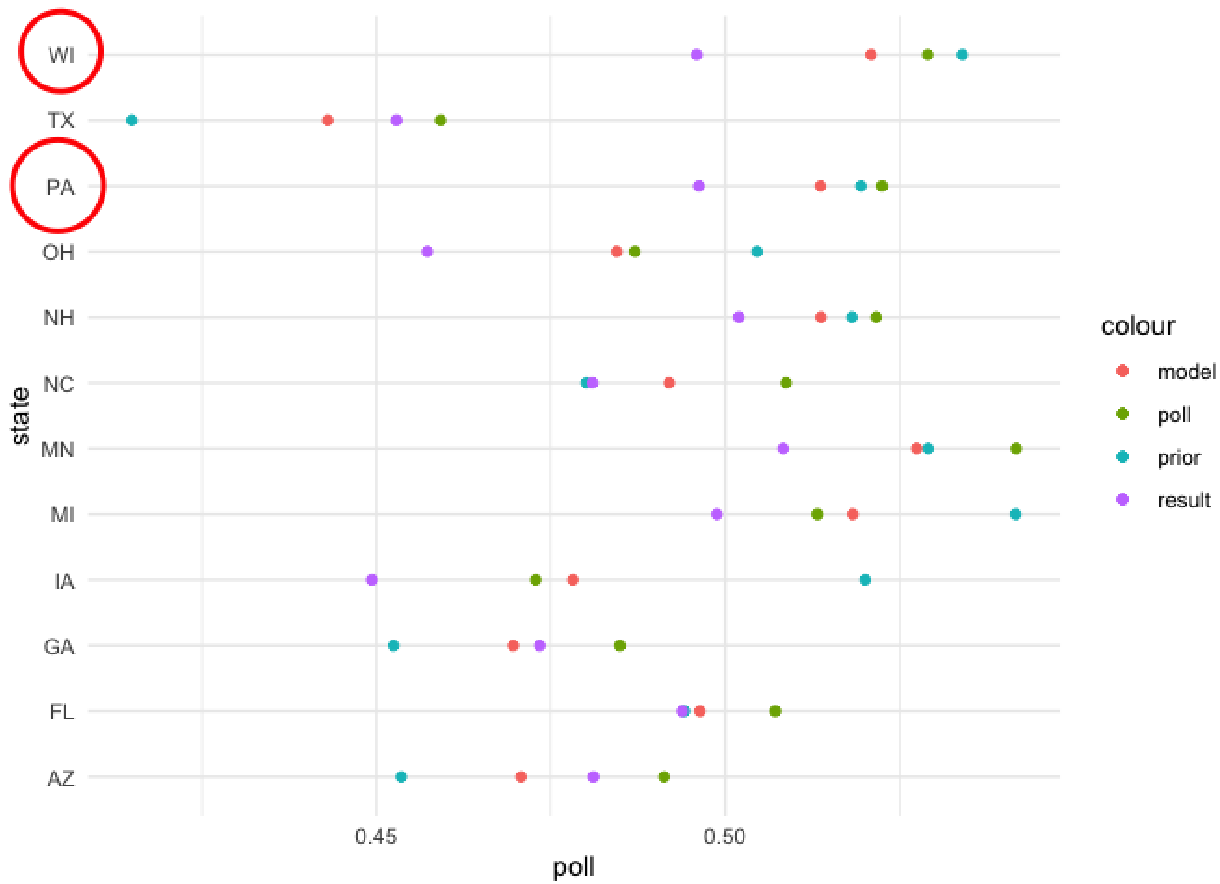
- Pollster firm (so-called "house effects")
- Poll mode
- Poll population

iii. Correcting for partisan non-response

- Whether a pollster weights by party registration or past vote
- Incorporated as a residual AR process

Debiased predictions

Notable improvements from partisan non-responseand other weighting issues



Debiased predictions

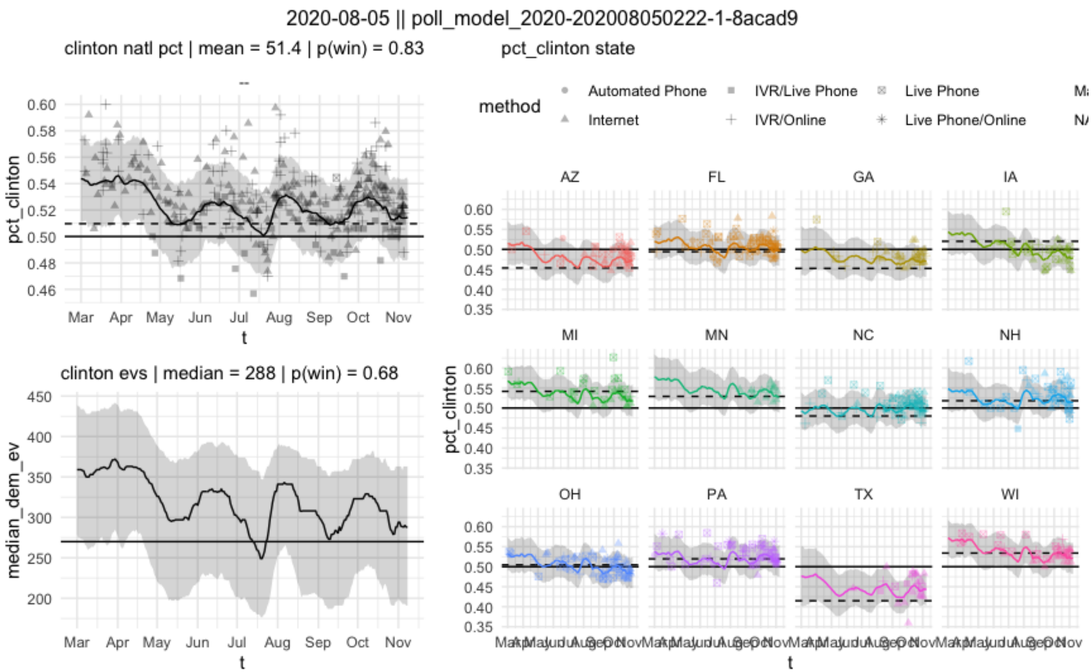
Notable improvements from partisan non-responseand other weighting issues

outlet	ev_wtd_brier	unwtd_brier	states_correct
economist (backtest)	0.0725679	0.0508319	48
538 polls-plus	0.0928000	0.0664000	46
538 polls-only	0.0936000	0.0672000	46
princeton	0.1169000	0.0744000	47
nyt upshot	0.1208000	0.0801000	46
kremp/slate	0.1210000	0.0766000	46
pollsavvy	0.1219000	0.0794000	46
predictwise markets	0.1272000	0.0767000	46
predictwise overall	0.1276000	0.0783000	46
desart and holbrook	0.1279000	0.0825000	44
daily kos	0.1439000	0.0864000	46
huffpost	0.1505000	0.0892000	46

Tying it all together

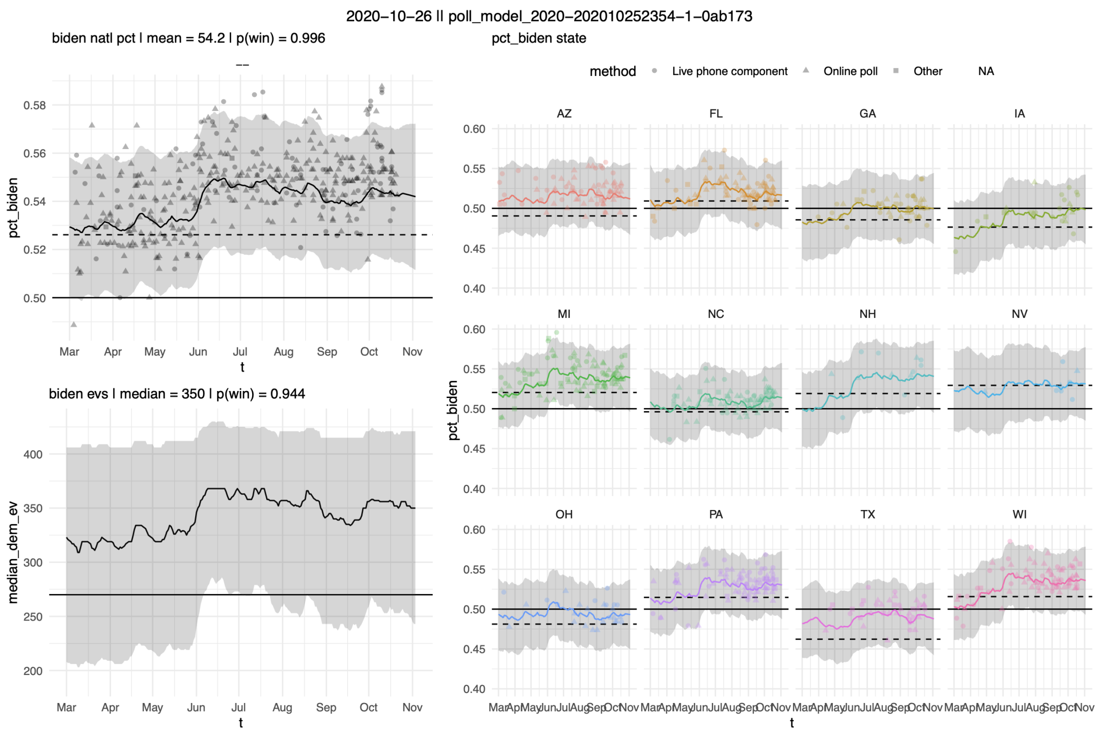
Tying it all together

1. 2016 election-day forecast:



Tying it all together

2. 2020 forecast*:



**As of October 26th, 2020*

Q&A

Thank you!

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These slides were made with the xaringan package for R from Yihui Xie. They are available online at https://www.gelliottmorris.com/slides/2020-10-26-mit/