

Forecasting the 2012 Presidential Election from History and the Polls

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The 2012 Presidential Election: *Obama 332–Romney 206*

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But also: *Nerds 1–Pundits 0*

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Analyst forecasts based on history and the polls

Drew Linzer, Emory University	332-206
Simon Jackman, Stanford University	332-206
Josh Putnam, Davidson College	332-206
Nate Silver, New York Times	332-206
Sam Wang, Princeton University	303-235

Pundit forecasts based on intuition and gut instinct

Karl Rove, Fox News	259-279
Newt Gingrich, Republican politician	223-315
Michael Barone, Washington Examiner	223-315
George Will, Washington Post	217-321
Steve Forbes, Forbes Magazine	217-321

What we want: Accurate forecasts as early as possible

The problem:

- The data that are available early aren't accurate:
Fundamental variables (economy, approval, incumbency)
- The data that are accurate aren't available early:
Late-campaign state-level public opinion polls
- The polls contain sampling error, house effects, and most states aren't even polled on most days

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The solution:

- A statistical model that uses what we know about presidential campaigns to update forecasts from the polls in real time

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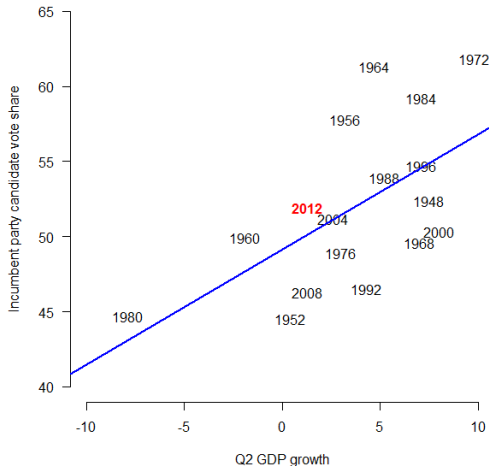
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What do we know?

1. The *fundamentals* predict national outcomes, noisily

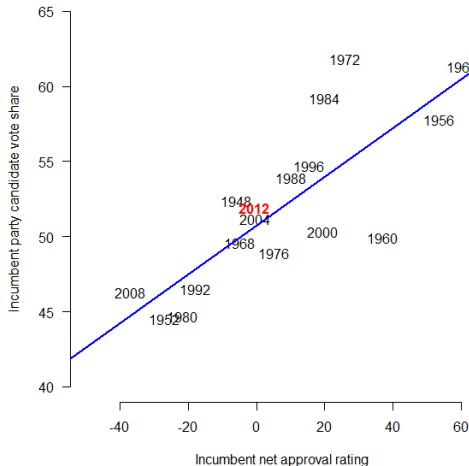
Election year economic growth



Source: U.S. Bureau of Economic Analysis

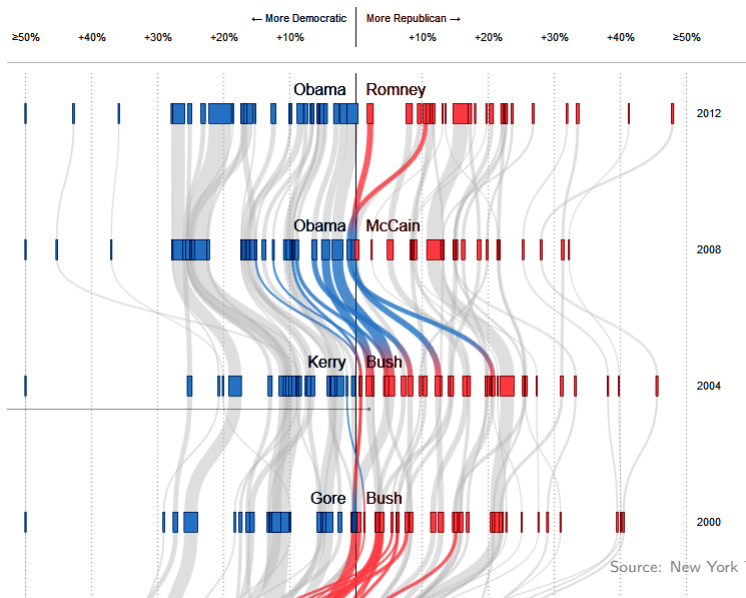
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Presidential approval, June

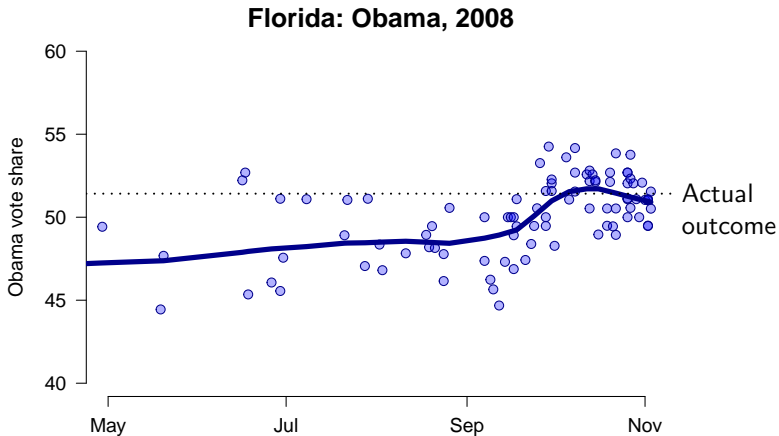


Source: Gallup

2. States vote outcomes swing (mostly) in tandem



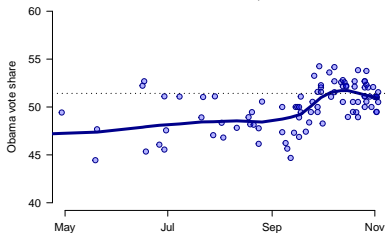
3. Polls are accurate on Election Day; maybe not before



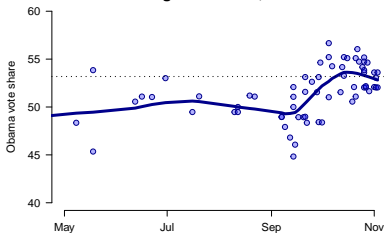
Source: HuffPost-Pollster

4. Voter preferences evolve in similar ways across states

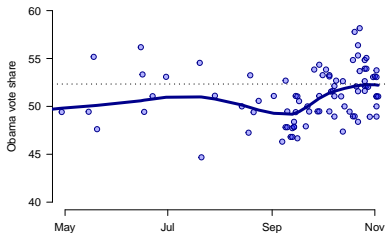
Florida: Obama, 2008



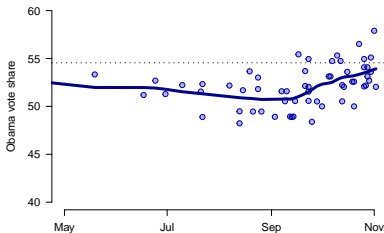
Virginia: Obama, 2008



Ohio: Obama, 2008

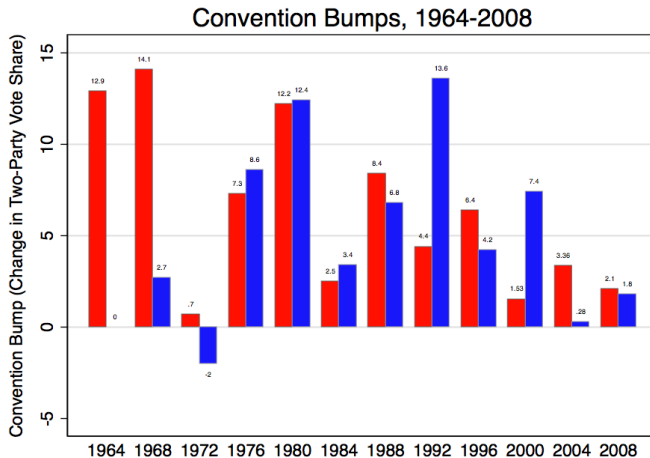


Colorado: Obama, 2008



Source: HuffPost-Pollster

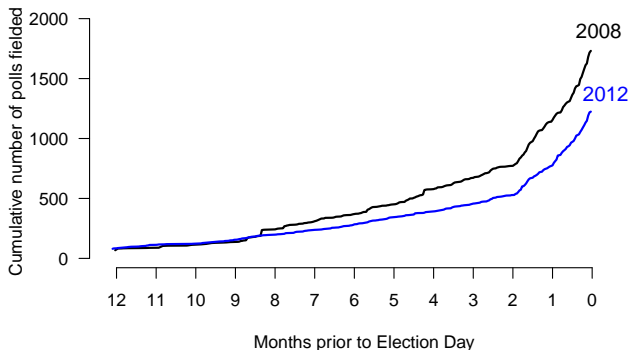
5. Voters have short term reactions to big campaign events



Data are from Campbell, Cherry, and Wink (1992); Holbrook (1996); Public Perspective, PollingReport.com, and Pollster.com

All together: A forecasting model that learns from the polls

Publicly available state polls during the campaign



Forecasts weight fundamentals \longleftrightarrow Forecasts weight polls

First, create a baseline forecast of each state outcome

Abramowitz *Time-for-Change* regression makes a *national* forecast:

$$\begin{aligned}\text{Incumbent vote share} &= 51.5 + 0.6 \text{ Q2 GDP growth} \\ &\quad + 0.1 \text{ June net approval} \\ &\quad - 4.3 \text{ In office two+ terms}\end{aligned}$$

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Use *uniform swing* assumption to translate to the state level:

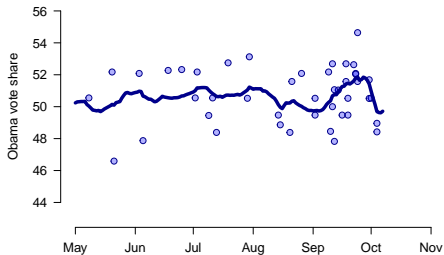
Subtract 1.5% for Obama from his 2008 state vote shares

Make this a Bayesian prior over the final state outcomes

Combine polls across days *and* states to estimate trends

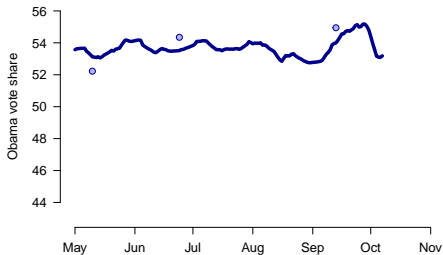
States with many polls

Florida: Obama, 2012



States with fewer polls

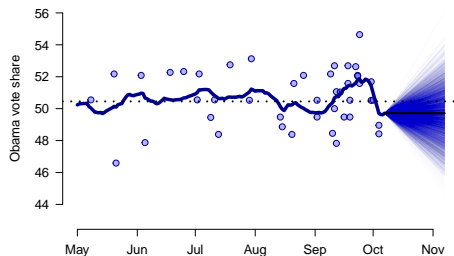
Oregon: Obama, 2012



Combine with baseline forecasts to guide future projections

Random walk (no)

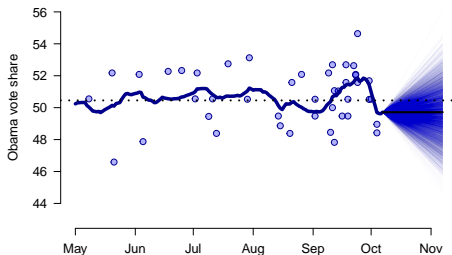
Florida: Obama, 2012



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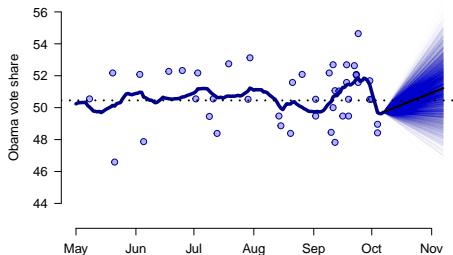
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Florida: Obama, 2012



Mean reversion

Florida: Obama, 2012



Forecasts compromise between history and the polls

A dynamic Bayesian forecasting model

Model specification

$$y_k \sim \text{Binomial}(\pi_{i[k]j[k]}, n_k)$$

Number of people preferring Democrat in survey k , in state i , on day j

$$\pi_{ij} = \text{logit}^{-1}(\beta_{ij} + \delta_j)$$

Proportion reporting support for the Democrat in state i on day j

National effects: δ_j

State components: β_{ij}

Election forecasts: $\hat{\pi}_{iJ}$

Priors

$$\beta_{iJ} \sim N(\text{logit}(h_i), \tau_i)$$

Informative prior on Election Day, using historical predictions h_i , precisions τ_i

$$\delta_J \equiv 0$$

Polls assumed accurate, on average

$$\beta_{ij} \sim N(\beta_{i(j+1)}, \sigma_\beta^2)$$

Reverse random walk, states

$$\delta_j \sim N(\delta_{(j+1)}, \sigma_\delta^2)$$

Reverse random walk, national

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Estimated for all states simultaneously

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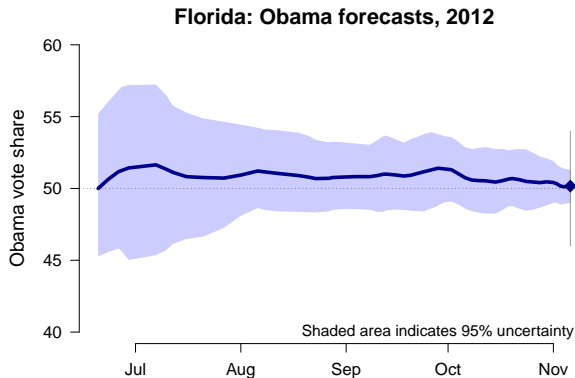
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Reverse random walk, states

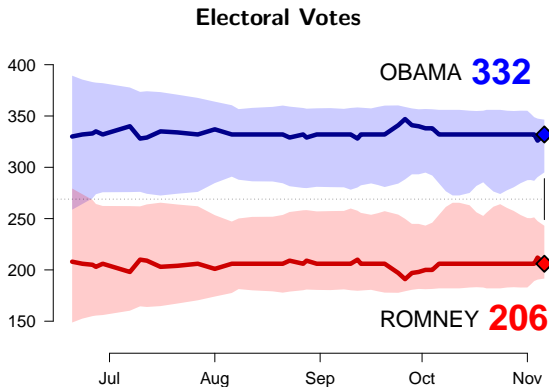
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Reverse random walk, national

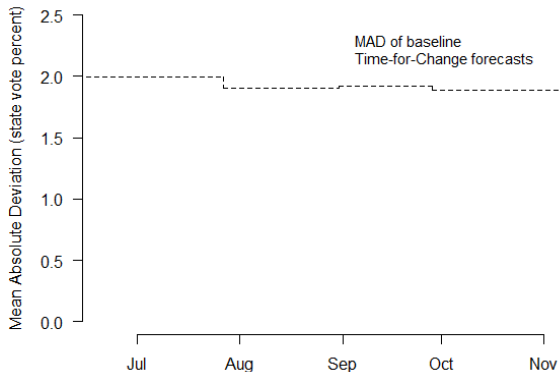
Results: Anchoring to the fundamentals stabilizes forecasts



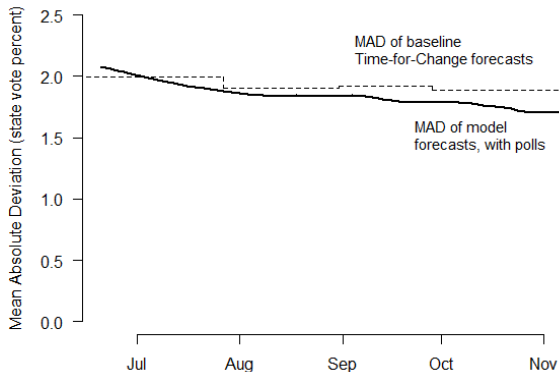
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There were almost no surprises in 2012

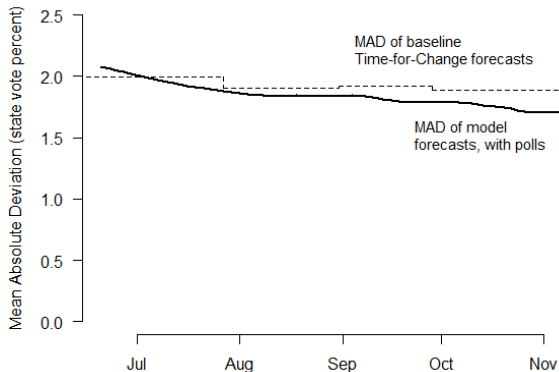


There were almost no surprises in 2012



On Election Day, average error = 1.7%

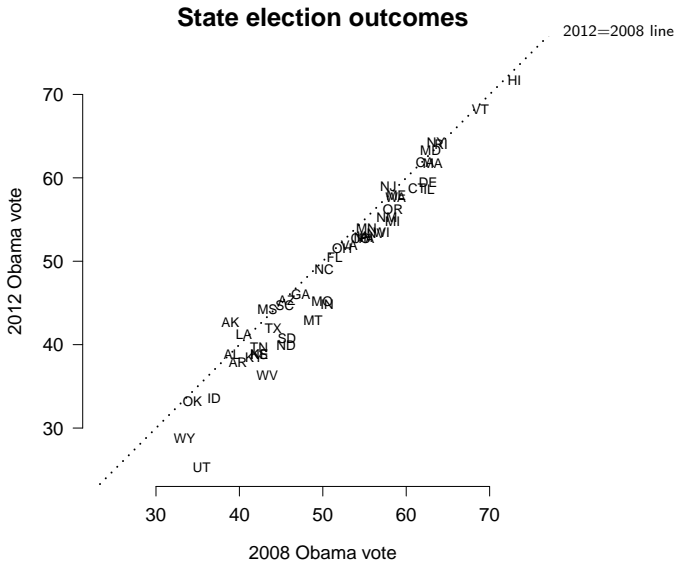
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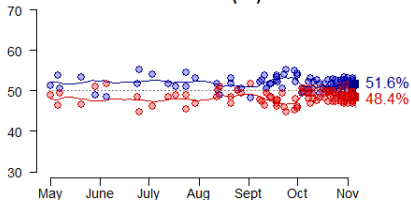
Why didn't the model improve forecasts by more?

The fundamentals and uniform swing were right on target

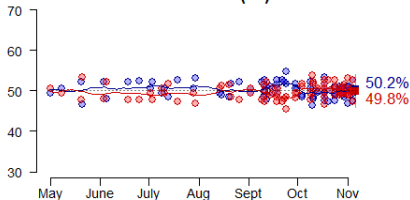


Aggregate preferences were *very* stable

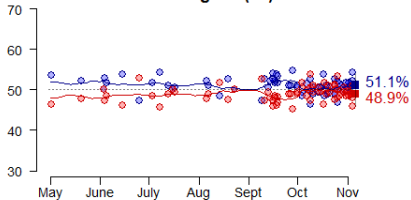
Ohio (96)



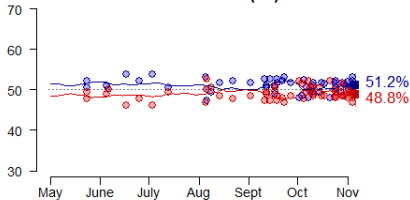
Florida (87)



Virginia (72)



Colorado (57)



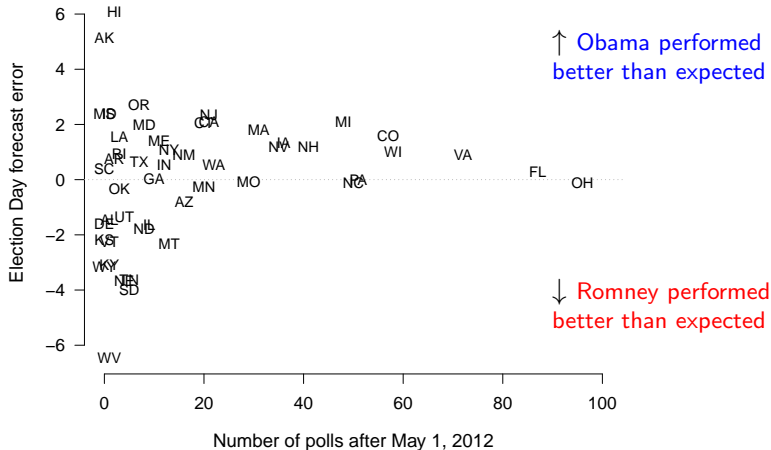
Percent supporting:

● Obama

● Romney

Could the model have done better? Yes

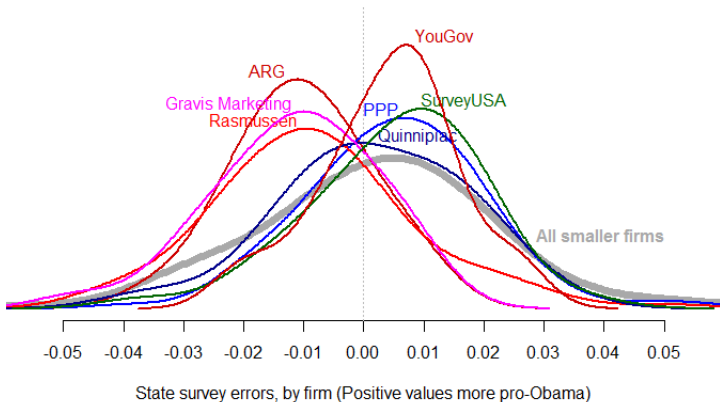
Difference between actual and predicted vote outcomes



Forecasting is only one of many applications for the model

- 1 Who's going to win?
- 2 Which states are going to be competitive?
- 3 What are current voter preferences in each state?
- 4 How much does opinion fluctuate during a campaign?
- 5 What effect does campaign news/activity have on opinion?
- 6 Are changes in preferences primarily national or local?
- 7 How useful are historical factors vs. polls for forecasting?
- 8 How early can accurate forecasts be made?
- 9 Were some survey firms biased in one direction or the other?

House effects (biases) were evident during the campaign



Much more at votamatic.org

✉ drew@votamatic.org

🐦 [@DrewLinzer](https://twitter.com/DrewLinzer)