Dynamic Bayesian Forecasting of Presidential Elections in the States

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Abstract

I present a dynamic Bayesian forecasting model that enables early and accurate prediction of U.S. presidential election outcomes at the state level. The method systematically combines information from historical forecasting models in real time with results from the large number of state-level opinion surveys that are released publicly during the campaign. The result is a set of forecasts that are initially as good as the historical model, then gradually increase in accuracy as Election Day nears. I employ a hierarchical specification to overcome the limitation that not every state is polled on every day, allowing the model to borrow strength both across states and, through the use of random-walk priors, across time. The model also filters away day-to-day variation in the polls due to sampling error and national campaign effects, which enables daily tracking of voter preferences towards the presidential candidates at the state and national levels. Simulation techniques are used to estimate the candidates' probability of winning each state and, consequently, a majority of votes in the Electoral College. I apply the model to pre-election polls from the 2008 presidential campaign and demonstrate that the victory of Barack Obama was never realistically in doubt. The model is currently ready to be deployed for forecasting the outcome of the 2012 presidential election.

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1 Introduction

Every four years, American political pundits and analysts spend endless hours dissecting the presidential election campaign and trying to forecast the winner. These efforts increasingly rely upon the interpretation of quantitative historical data and the results of pre-election (or *trial-heat*) public opinion polls asking voters their preferred candidate for president. The 2008 presidential campaign in particular witnessed a remarkable increase in the number of pre-election polls conducted at the *state* level, where presidential elections are ultimately decided. By Election Day, over 1,700 distinct state-level surveys had been published by media organizations and private polling firms, in every U.S. state, totaling over one million individual interviews (*Pollster.com* 2008). In the most competitive *swing* states, new polls were released almost daily as Election Day neared. The widespread availability of these survey findings critically shaped both how the campaign was reported in the news media as well as how the presidential candidates were perceived by voters (Pew Research Center 2008, Becker 2008, Traugott and Lavrakas 2008).

State-level pre-election survey data represent a rich—if extremely noisy—new source of information for both forecasting election outcomes and tracking the evolution of voter preferences during the campaign. Interest in measuring and predicting these outcomes is not limited to those in the media whose job it is to explain campaign trends to the public (Broh 1980, Stovall and Solomon 1984, Rhee 1996, Rosenstiel 2005). Political strategists who make decisions about the allocation of hundreds of millions of dollars worth of advertising and manpower need to be able to ascertain candidates' relative positioning in the electorate, and their potential to carry various states on the way to winning the presidency (Center for Responsive Politics 2008, Jamieson 2009). In addition, academic researchers have long been interested in the factors that predict presidential election outcomes (e.g., Lewis-Beck and Rice 1992, Campbell and Garand 2000), the forecasting value of historical models versus pre-election public opinion polls (Brown and Chappell 1999, Holbrook and DeSart 1999), the earliness with which accurate forecasts can be made (Gelman and King 1993, Erikson and Wlezien 1996, Wlezien and Erikson 1996), the dynamics behind public opinion during the campaign (Campbell, Cherry and Wink 1992, Romer et al. 2006, Erikson and Wlezien 1999, Wlezien and Erikson 2002, Panagopoulos 2009*a*), and the extent to which campaigns affect the eventual result (Shaw 1999, Hillygus and Jackman 2003, Vavreck 2009). The aim of this paper is to produce quantities of interest to each of these constituencies: state- *and* national-level estimates of not only the *current* preferences of voters at every point in the campaign; but also *forecasts* of presidential candidates' vote shares and probabilities of victory on Election Day.

I introduce a dynamic Bayesian forecasting model that unifies the regression-based historical forecasting approach developed in political science and economics with the poll-tracking capabilities made feasible by the recent upsurge in state-level opinion polling. Existing historical models are designed to predict presidential candidates' popular vote shares, at a single point in time—usually two to three months in advance of an election—from structural "fundamentals" such as levels of economic growth, changes in unemployment rates, whether the incumbent is running for re-election, and so forth (e.g., Bartels and Zaller 2001, Abramowitz 2008, Campbell 2008*b*, Erikson and Wlezien 2008, Fair 2009). In line with theories of retrospective voting, voters tend to punish incumbent party candidates when times are bad, and reward them when economic and social conditions are more favorable (Kinder and Kiewiet 1991, Nadeau and Lewis-Beck 2001, Duch and Stevenson 2008).

Although predictions from structural models can be surprisingly accurate, they are also subject to a large amount of uncertainty. Most historical forecasts are based on data from just 10 to 15 past elections, and many only generate national-level estimates of candidates' vote shares. Unless the fundamentals clearly favor one candidate over the other, it is difficult for structural models to confidently predict the election *winner*. Moreover, in the event that an early forecast is in error, structural models contain no mechanism for updating predictions once new information becomes available closer to

Election Day. In 2008, for example, Democrat Barack Obama won the presidency with 53.7% of the major-party vote—a sizeable margin, by historical standards. Yet many published forecasts were unsure of an Obama victory. Two months before the election, Erikson and Wlezien (2008) gave Obama a 72% chance of winning. Lewis-Beck and Tien (2008) judged the race to be a toss-up. Campbell (2008*b*) predicted that Republican John McCain would win, with 83% probability. In closer elections, the problem is amplified: political scientists completely failed to predict the victory of Republican George W. Bush in 2000 (Campbell 2001).

Pre-election polls provide contextual information that can be used to correct potential errors in historical forecasts, increasing both their accuracy and their precision. Polls conducted just before an election generate estimates that are very close to the eventual result, on average (Traugott 2001; 2005, Pickup and Johnston 2008, Panagopoulos 2009*b*). Earlier in the campaign, polls are less effective for forecasting (e.g., Campbell and Wink 1990, Gelman and King 1993, Campbell 1996), but remain useful for detecting trends in voter preferences. Survey-based opinion tracking presents certain challenges, however. First, not every state is polled on every day, leading to gaps in the time series. Data are especially sparse in less-competitive states and early in the campaign. Second, measured preferences fluctuate greatly from poll to poll, due to sampling variability and other sources of error. Such swings have been prone to misinterpretation as representing actual changes in attitudes. Some amount of multi-survey aggregation and smoothing is therefore necessary to reveal any underlying trends (Erikson and Wlezien 1999, Jackman 2005, Wlezien and Erikson 2007).

The integrated modeling framework that I describe will enable researchers to refine and update structural state-level election forecasts in real time, using the results of every newly available state-level opinion poll. Older polls that contribute less to the forecast are used to estimate past trends in state-level opinion. To handle the uneven spacing of pre-election polls, the model borrows strength hierarchically across both states *and* days of the campaign. It also detects and accounts for campaign effects due to party conventions or major news events that influence mass opinion in the short term, but may or may not be related to the election outcome (Finkel 1993, Holbrook 1994, Shaw 1999, Wlezien and Erikson 2001).

The result is a set of election forecasts that are produced early in the campaign, become increasingly accurate as Election Day nears, yet remain relatively stable over time. Because these forecasts depend on reported levels of support for each candidate in the trial-heat polls, my model also yields daily estimates of *current* opinion in each state at any point during the campaign, with associated measures of uncertainty. The model further generates logically valid estimates of the probabilities that either candidate will win each state and the Electoral College vote as a whole, as a function of the available polling data, the prior certainty in the predictions of the historical model, and the proximity to Election Day.

I apply the model to the dual problems of tracking state-level opinion and forecasting the outcome of the 2008 U.S. presidential election, using the benefit of hindsight to evaluate model performance. I simulate the campaign from May 2008 through Election Day, November 4, updating the model estimates from each new poll as they are released. Contrary to much of the media commentary at the time, Obama's victory was highly predictable many months in advance of the election.

2 Research Background

Presidential elections in the United States are decided at the state level, through the institution of the Electoral College. Within each state, candidates are awarded electoral votes on a winner-take-all basis, with the number of electoral votes per state equal to a state's total number of federal Representatives and Senators. (There are minor exceptions to this rule in Maine and Nebraska.) The candidate receiving a majority of electoral votes wins the election. In recent elections, outcomes in most states have not been competitive.

In these *safe* states, the winning candidate is largely predetermined, even if the exact percentage of the vote that each candidate will receive remains unknown. The division of the country into Republican "red states" and Democratic "blue states" has been much remarked upon (e.g., Farhi 2004, Dickerson 2008). Most observers consider 30 to 35 of the fifty states to be safe, with each side containing a similar number of electoral votes.

Presidential elections are, as a result, effectively won or lost in a smaller number of pivotal *swing* or *battleground* states. Florida and Ohio stand out as the most prominent recent examples. Outcomes in these states are, by their very nature, both more important—and more difficult—to predict in advance. It is especially in the swing states where the potential value of pre-election polling to forecasting and opinion tracking is the greatest.

2.1 Characteristics of Trial-Heat Polls

Pre-election polls are typically conducted as random samples of registered or "likely" voters who are asked their current preferences among the presidential candidates. The wording of the 2008 Washington Post-ABC News tracking poll, for example, read "If the 2008 presidential election were being held today and the candidates were Barack Obama and Joe Biden, the Democrats, and John McCain and Sarah Palin, the Republicans, for whom would you vote?" Pollsters tabulate the answers to this question and report the percentages of voters providing each response. Most polls also record the percentage of voters who are undecided; others tally support for non-major party candidates as well.

Many factors can cause the results of a survey to deviate from a state's actual vote outcome. Sampling variability is the largest single source of error, accounting for half or more of the total variation in trial-heat estimates during the campaign (Erikson and Wlezien 1999, Wlezien and Erikson 2002). In addition, differences between polling organizations in survey design, question wording, sampling weights, and so forth all contribute to the larger *total* survey error (Weisberg 2005, Biemer 2010). *House effects* arise when polling firms produce survey estimates that are systematically more or less favorable to particular parties or candidates (McDermott and Frankovic 2003, Wlezien and Erikson 2007). Fortunately, the bias arising from such effects usually cancels out by averaging over multiple concurrent surveys by different pollsters (Traugott and Wlezien 2009). Anomalous survey results will be most damaging to estimates of state opinion when there are few other polls to validate against.

The timing of polls also affects their predictive accuracy. Polls fielded early in the campaign are much more weakly correlated with the election outcome than polls conducted just before Election Day. During the race, voters' reported preferences fluctuate in response to salient campaign events, and as they learn more about the candidates (Gelman and King 1993, Arceneaux 2006, Stevenson and Vavreck 2000). For voters who are undecided or who have devoted minimal effort to evaluating the candidates, intense and consistently favorable media coverage of one of the candidates—as occurs during the party conventions, for example—can sway individuals to report preferences that differ from their eventual vote choice (Zaller 1992). Many voters simply wait until the end of the campaign to make up their mind.

2.2 Current Survey-Based Approaches to Forecasting

One approach to utilizing pre-election polls for election forecasting is to include early measures of presidential approval, policy satisfaction, support for the incumbent party candidate, or other relevant attitude as an independent variable in a broader historical model fitted to past election data (e.g., Campbell 2008*b*, Erikson and Wlezien 2008). The primary limitation of this method is that, as emphasized by Holbrook and DeSart (1999), the regression weights estimated for the opinion variable are subject to uncertainty (sample sizes are typically small), and may have changed since earlier elections. The poll results used as inputs for the model will also contain error, and may differ from the true state of opinion at any point in the campaign.

A second strategy uses trial-heat survey data to update historical model-based forecasts in a Bayesian manner (e.g., Brown and Chappell 1999, Strauss 2007, Rigdon et al. 2009, Lock and Gelman 2010). Yet no current methods are general enough to utilize data from all available state-level opinion polls in real time. Bayesian techniques for estimating trends in voter preferences using pre-election polls either do not produce forecasts until very late in the campaign (Christensen and Florence 2008), or require that the election outcome is already known (Jackman 2005), making forecasting impossible.

3 A Dynamic Bayesian Forecasting Model

I show how a sequence of state-level pre-election polls can be used to estimate both current voter preferences and forecasts of the election outcome, for every state on every day of the campaign, regardless of whether a survey was conducted on that day. Forecasts from the model gradually transition from being based upon historical factors early in the campaign, to survey data closer to Election Day. In states where polling is infrequent, the model borrows strength hierarchically across both states and time, to estimate smoothed within-state trends in opinion between consecutive surveys. This is possible because national campaign events tend to affect short-term voter preferences in all fifty states in a consistent manner. The temporal patterns in state-level opinion are therefore often similar across states.

3.1 Specification

Denote as h_i a forecast of the vote share received by the Democratic Party candidate in states $i = 1 \ldots 50$, based upon a historical model that produces predictions far in advance of Election Day. There are a variety of approaches to generating these baseline forecasts (e.g., Rosenstone 1983, Holbrook 1991, Campbell 1992, Lock and Gelman 2010). Since no definitive model exists, the choice of how to estimate h_i—as well as how much prior certainty to place in those estimates—is left to the analyst. Values chosen for h_i should be theoretically well-motivated, however, as they will be used to specify an informative Bayesian prior for the estimate of each state's election outcome, to be updated using polling data gathered closer to the election.

As the campaign progresses, increasing numbers of pre-election polls are released. Let $j = 1 \ldots J$ index days of the campaign, so that $j = 1$ corresponds to the first day of polling and $j = J$ is Election Day. The model can be fitted on any day of the campaign, using as many polls are presently available. The J days prior to Election Day need not include the dates of every pre-election poll, if an investigator wishes to disregard polls conducted far ahead of the election. On day j of the campaign, let K_j represent the total number of state-level polls that have been published until that point. Denote the number of respondents who report a preference for one of the two major party candidates in the kth survey ($k = 1 \ldots K_j$) as n_k, and let y_k be the number who support the Democratic candidate.

The proportion of voters in state i on day j who would tell pollsters that they intend to vote for the Democrat, among those with a current preference, is denoted π_{ij}. Assuming a random sample,

$$y_k \sim \text{Binomial}(\pi_{i[k]j[k]}, n_k), \tag{1}$$

where $i[k]$ and $j[k]$ indicate the state and day of poll k. In practice, house effects and other sources of survey error will make the observed proportions y_k/n_k overdispersed relative to the nominal sample sizes n. As I will demonstrate, the amount of overconfidence that this produces in the model's election forecasts is minimal. Correcting for overdispersion by estimating firm-specific effects is impractical because most pollsters only conduct a very small share of the surveys. Alternatively, deflating n_k and y_k by a multiplicative factor will lead to underestimation of the temporal volatility in π_{ij}, which actually worsens the problem of overconfidence in the election forecasts.

The Election Day forecast in state i is the estimated value of π_{iJ}. On any day during the campaign, π_{ij} are estimated for *all* J days, both preceding and following the most recent day on which a poll was conducted. As voter preferences vary during the campaign, estimates of π_{ij} are only expected to approximate the vote outcome for j close to J. Undecided voters are excluded from the analysis because it is not known how they would vote either on day j (if forced to decide), or on Election Day. If undecided voters disproportionately break in favor of one candidate or the other, it will appear as a systematic error in estimates of π_{iJ} once data have been collected through day J. The results I present do not show evidence of such bias.

The daily π_{ij} are modeled as a function of two components: a state-level effect β_{ij} that captures the long-term dynamics of voter preferences in state i; and a national-level effect δ_j that detects systematic departures from β_{ij} on day j, due to short-term campaign factors that influence attitudes in every state by the same amount:

$$\pi_{ij} = \text{logit}^{-1}(\beta_{ij} + \delta_j). \tag{2}$$

I place both β_{ij} and δ_j on the logit scale, as π_{ij} is bounded by zero and one. Values of $\delta_j < 0$ indicate that on average, the Democratic candidate is polling below the election forecast; $\delta_j > 0$ indicates that the Democrat is running ahead of the forecast.

Separating the state- from national-level effects enables the model to borrow strength across states when estimating π_{ij}. The trends in all states' π_{ij} are estimated simultaneously. However, each state will have intervals when no polls are conducted. To help fill these gaps, the δ_j parameter detects common patterns in the multivariate time series of voter opinion in other states on day j. If and when opinions across states do not trend together, this will also be detectable by the model.

I anchor the scales of β_{ij} and δ_j on Election Day by fixing $\delta_J \equiv 0$. This is an identifying restriction that implies $\pi_{iJ} = \text{logit}^{-1}(\beta_{iJ})$. State-level historical forecasts h_i are then incorporated into the model through an informative Normal prior distribution over β_{iJ},

$$\beta_{iJ} \sim N(\text{logit}(h_i), s_i^2). \tag{3}$$

Denote the prior precision as $\tau_i = s_i^{-2}$. The τ_i are specified by the analyst. Smaller values of τ_i indicate less certainty in the respective h_i, which upweights the influence of the polling data on estimates of β_{iJ} and π_{iJ}. Larger values of τ_i place greater certainty in the historical forecast and make estimates of β_{iJ} and π_{iJ} less sensitive to new polling data. Overconfidence in h_i can lead to misleadingly small posterior credible intervals around estimated $\hat{\pi}_{iJ}$, so caution is required. A sensitivity analysis in Section 4.4 indicates that τ_i should not generally exceed 20.

When estimating π_{iJ} weeks or months ahead of the election, there will be a gap in the polling data between the last published survey and Election Day. To bridge this interval, as well as to connect the days in each state when no polls are released, both β_{ij} and δ_j are assigned a Bayesian reverse random-walk prior, "beginning" on Election Day. The idea is similar to Strauss (2007). As shown by Gelman and King (1993), although historical model-based forecasts can help predict where voters' preferences *end up* on Election Day, it is not known in advance what path they will take to get there. Each day's estimate of β_{ij} is given the prior distribution

$$\beta_{ij} | \beta_{i,j+1} \sim N(\beta_{i,j+1}, \sigma_\beta^2), \tag{4}$$

where the estimated variance σ_β^2 captures the rate of daily change in β_{ij}. Likewise,

$$\delta_j | \delta_{j+1} \sim N(\delta_{j+1}, \sigma_\delta^2) \tag{5}$$

where σ_δ^2 captures the rate of daily change in δ_j. Both σ_β and σ_δ are given a uniform prior distribution.

3.2 Interpretation

The Election Day forecast in each state is a compromise between the most recent poll results and the predictions of the structural model. Posterior uncertainty in π_{iJ} will depend on the prior τ_i, the number and size of the available polls, and the proximity to Election Day. On day $j < J$ of the campaign, the forward trend in β_{ij} shrinks via the reverse random-walk process towards the prior distribution of β_{iJ}. The δ_j similarly converge ahead to $\delta_J \equiv 0$. If the election is soon, δ_j will already be near zero, and β_{ij} will have little time to "revert" to the structural prior (Equation 3). As a result, estimates of π_{iJ} will be based primarily on each state's survey data.

For forecasts of π_{iJ} made farther ahead of the election, the forward path of π_{ij} after polling ends is more dependent on the structural prior. If τ_i is large, β_{ij} converges quickly to $\text{logit}(h_i)$, so π_{iJ} converges to h_i. If τ_i is smaller, the forward sequence in β_{ij} moves more slowly away from its value on day j, so future estimates of π_{ij} will be driven by the trend in δ_j as it returns to zero on day J. Candidates who are running behind the forecast ($\delta_j < 0$) will gain support, while those who are ahead of the forecast ($\delta_j > 0$) will trend downwards.

As older polls are superseded by newer information, they contribute less to the forecast, but they leave behind the historical trends in β_{ij} and δ_j up to the current day of the campaign. Combining the daily estimates of β_{ij} and δ_j (Equation 2) produces estimates of underlying state voter preferences π_{ij} over the duration of the campaign. This series is both important to analysts and useful for posterior model checking of proper fit of the model to the data. Past estimates of δ_j indicate the magnitude and direction of national campaign effects. Comparing the trends in δ_j to β_{ij} reveals the relative volatility in voters' preferences due to state- or national-level factors. Changes in the filtered state-level preferences β_{ij} can also suggest evidence of successful local campaign activity, as distinct from national-level shifts in opinion.

In studies where the result of the election is known, as when researching trends in voter preferences from past elections, h_i can be set equal to the outcome in state i. We would then fix $\beta_{iJ} \equiv \text{logit}(h_i)$ instead of specifying the prior distribution in Equation 3, since forecasting (based upon estimating π_{iJ}) is no longer of interest.

3.3 Estimation

Given K_j state-level pre-election polls, and fifty historical forecasts h_i with prior precision τ_i, the Bayesian model may be estimated using a MCMC sampling procedure. I implement the estimator in the WinBUGS and R software packages (Lunn et al. 2000, Sturtz, Ligges and Gelman 2005, R Development Core Team 2011). This produces a rich (and large) set of parameter estimates: the average preferences of voters, π_{ij}, as they would be reported to pollsters in each state at each day in the campaign, the trend in national-level campaign effects δ_j, the filtered state-level vote preferences β_{ij}, and the state-level Election Day forecasts, π_{iJ}. Measures of uncertainty for each estimated parameter are based on the spread of the simulated posterior draws.

One limitation is that for forecasts made far in advance of Election Day, the model becomes slow to converge due to the lack of available polling data. A slight modification to the specification of the β_{ij} parameters makes the problem tractable and accelerates MCMC convergence. Rather than let β_{ij} vary by day, I divide the J days of the campaign into J/W short spans or *windows* of W days apiece. In Equation 2, I replace β_{ij} with $\beta_{it[j]}$, which denotes the value of β in state i for the time period $t = 1 \ldots J/W$ containing day j. The prior distribution in Equation 3 is assigned to $\beta_{it[J]}$. Parameters δ_j are still estimated for each of the J days of the campaign, and the election forecast remains π_{iJ}. Values of W equal to just three to five days can significantly improve the estimation process, without substantively altering the election forecast. This simplification works because while δ_j fluctuates quite a bit on a day-to-day basis, β_{ij} changes far more gradually over time (see Figure 8).

Following estimation, the posterior probability that the Democratic candidate will win the election in state i is calculated as the proportion of posterior draws of π_{iJ} that are greater than 0.5. The probability that the Democratic candidate wins the presidency can be similarly computed directly from the MCMC draws. An alternative approach using just the state probabilities was proposed by Kaplan and Barnett (2003). I select the fifty posterior draws of π_{iJ} produced in a single iteration of the sampling algorithm, and tally the total number of electoral votes in states where the Democratic candidate is forecast to receive more than 50% of the two-party vote. I then add the three electoral votes of the District of Columbia, which is reliably Democratic. Repeating this calculation across multiple sampling iterations produces a distribution of predicted electoral vote outcomes. The proportion of these outcomes in which the Democratic candidate receives an absolute majority—270 or more—of the 538 electoral votes is the Democratic candidate's probability of victory.

4 Application: The 2008 U.S. Presidential Election

The 2008 U.S. presidential election was widely predicted to result in a victory for Democrat Barack Obama (Campbell 2008*a*). The Republican candidate, John McCain, suffered from two major drags on his candidacy: an extremely low approval rating for the incumbent Republican president, George W. Bush; and a weak economy, whether measured in terms of GDP growth, consumer satisfaction, unemployment rates, or other factors. Yet as a candidate, Obama consistently lagged behind expectations in national pre-election polls—even falling behind McCain for a brief period after the Republican National Convention in early September (*Pollster.com* 2008). News reports quoted worried Democrats suddenly wondering if Obama would lose after all (e.g., Kuhn and Nichols 2008). Contributing to the uncertainty were the lingering effects of the unusually long Democratic primary battle between Obama and then-Senator Hillary Clinton; as well as questions

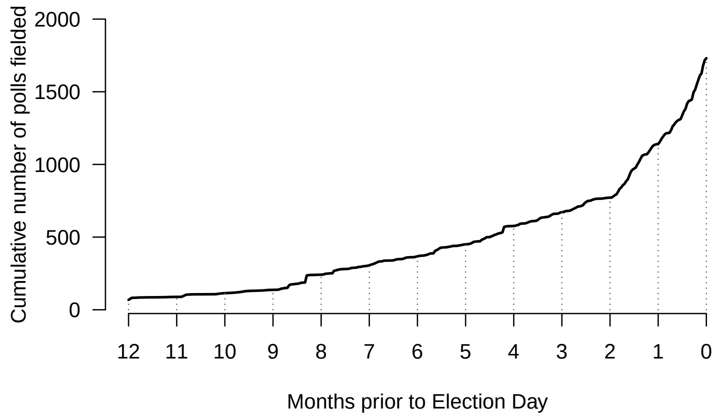

Figure 1: *Cumulative number of state-level presidential pre-election polls fielded in advance of the 2008 election. Source:* Pollster.com *(2008).*

about what effect Obama's race might have on the willingness of white voters to support him in the November election.

I simulate the process of forecasting the 2008 election and tracking state-level opinion in real time during the campaign, leading up to Election Day. This enables us to answer a series of key questions: By how much did voter preferences change over the course of the campaign? What were the short-term effects of campaign events on reported voter preferences? Which were the actual swing states and how soon was this knowable? Finally, how early, and with what precision, was the election outcome predictable from a combination of structural factors and pre-election polls?

4.1 State-level Polling Data

During the campaign, survey researchers and media organizations released the results of 1,731 state-level public opinion polls asking voters their current choice for president (*Pollster.com* 2008). The quantity of interest will be the Obama share of the state-level major party vote, measured as the proportion of respondents favoring Obama out of the total number supporting either Obama or McCain. Polls conducted during the primary season, before the nominations of Obama and McCain were assured, asked only about a hypothetical match-up between the two candidates.

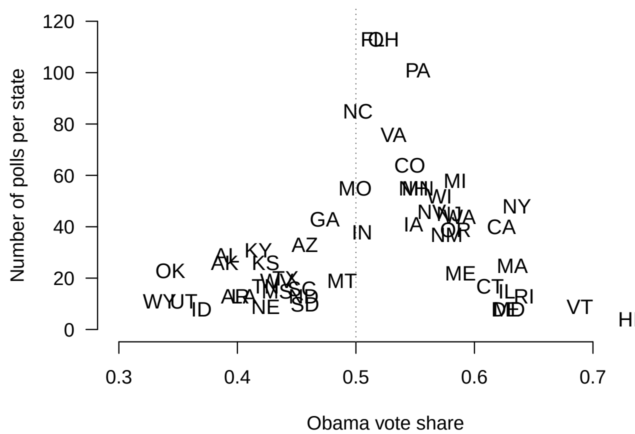

Figure 2: *More polls were fielded in states that were expected to be competitive, as indicated by the closeness of Obama's eventual vote share to 50%.*

More than 150 distinct entities published state-level polls in 2008. Although the median number of polls among all firms was just two, the seven most active firms—Rasmussen, SurveyUSA, the Quinnipiac University Poll, Research 2000, Zogby, American Research Group, and PPP—were responsible for 64% of the state surveys. The median survey contained 600 respondents. On average, 91% of those polled reported a preference for Obama or McCain; unsurprisingly, the proportion of undecided voters was larger in early polls and decreased closer to Election Day. As most polls spend multiple days in the field to complete the sample, I will consider each poll to have "occurred" on the final day in which interviews were conducted.

Towards the end of the campaign, the rate of pre-election polling accelerated, with more than half of all surveys being fielded in the final two months before Election Day (Figure 1). There were also more polls fielded in states that were expected to be closely competitive: Florida and Ohio were each surveyed 113 times, Pennsylvania was surveyed 101 times, and another 85 polls were conducted in North Carolina (Figure 2). On the low end, fewer than ten polls were conducted in Hawaii, Delaware, Maryland, and Vermont; all safe Democratic states—as well as in Idaho and Nebraska; both safe Republican states. States such as Missouri, Indiana, Georgia, and Montana are among the most interesting from a forecasting perspective because the outcomes in those states were very close despite being polled relatively infrequently.

4.2 The Historical Forecast

Forecasting presidential elections using a structural model imposes a tradeoff between earliness and accuracy. I produce both an inaccurate *early* forecast and an accurate *late* forecast based on the Abramowitz (2008) *Time-for-Change* model. The late forecast, available about ten weeks prior to Election Day, predicts the national-level vote share for the incumbent party candidate from three variables: the annualized growth rate of second quarter GDP, the June approval rating of the incumbent president, and a dummy for whether the incumbent party has been in office for two or more terms. For the earlier forecast, available up to six months in advance, I use a variation of the model fitted to changes in first quarter GDP, and the March presidential approval rating. I initially base structural forecasts on the early model, then switch to the late model as soon as it would have become available. From 15 previous presidential elections, the early forecast predicted Obama to receive 56.8% of the major-party vote in 2008. The more proximate late forecast predicted that Obama would receive 54.3%. Both forecasts overestimated Obama's actual vote share of 53.7%.

To translate national forecasts to the state level, I exploit a twenty-year pattern in presidential election outcomes. Since 1980, state-level Democratic vote shares have tended to rise and fall in national waves, by similar amounts across states. In 2004, Democrat John Kerry received 48.8% of the two-party presidential vote. Assuming the same trend would continue in 2008 (as it did), the Time-for-Change model predicts an average state-level gain by Obama of 8% early and 5.5% late.

I calculate h_i by first adding to Kerry's 2004 state-level vote shares either 5.5% or 8% depending upon the timing of the forecast. I then adjust the forecast by a further 6% in candidates' home states, adding in for Hawaii (Obama) and Texas (Bush in 2004), and subtracting away for Arizona (McCain) and Massachusetts (Kerry in 2004). This correction was estimated from past elections by Holbrook (1991) and Campbell (1992), and also employed by Lock and Gelman (2010). Compared to the actual result, the early Time-for-Change forecast had a state-level mean absolute deviation (MAD) of 3.4%, and the late forecast had a MAD of 2.6%. I set $\tau_i = 10$ for the early forecast, and a more confident $\tau_i = 20$ for the late forecast.

To test the sensitivity of the forecasts to the choice of h_i, I examine an alternative model based on the idea of a Democratic *normal vote*. For this, I set h_i equal to the mean Democratic vote share in each state over the previous four presidential elections: 1992 and 1996, which were won by Democrats, and 2000 and 2004, which were won by Republicans. In 2008, this would have systematically under-predicted Obama's vote share by 1.8%, on average, with a MAD of 4.2%. I hold $\tau_i = 10$.

4.3 Updating Forecasts Using Pre-Election Polls

I consider all state-level polls fielded within the final six months of the campaign. The first set of election forecasts are produced with four months remaining, in July 2008. I then move forward through Election Day, two weeks at a time. At each step, I update the election forecasts and estimates of current opinion using all newly available polls. In total, I fit the model nine times: with $16, 14, 12, \ldots, 2$ weeks left in the campaign, and again on Election Day. Parameter estimates are based on three sequences of 200,000 MCMC iterations, discarding the first half as burn-in and thinning to keep every 300th draw. I specify a three-day window ($W = 3$) for parameters $\beta_{it[j]}$. MCMC convergence is assessed by values of the Gelman-Rubin statistic $\hat{R} \approx 1$, and visual confirmation that the three sequences are completely mixed (Gelman and Rubin 1992, Brooks and Gelman 1998).

Three snapshots of estimates of $\hat{\pi}_{ij}$ in the competitive states of Florida and Indiana demonstrate the real-time performance of the model (Figure 3). Although a large number

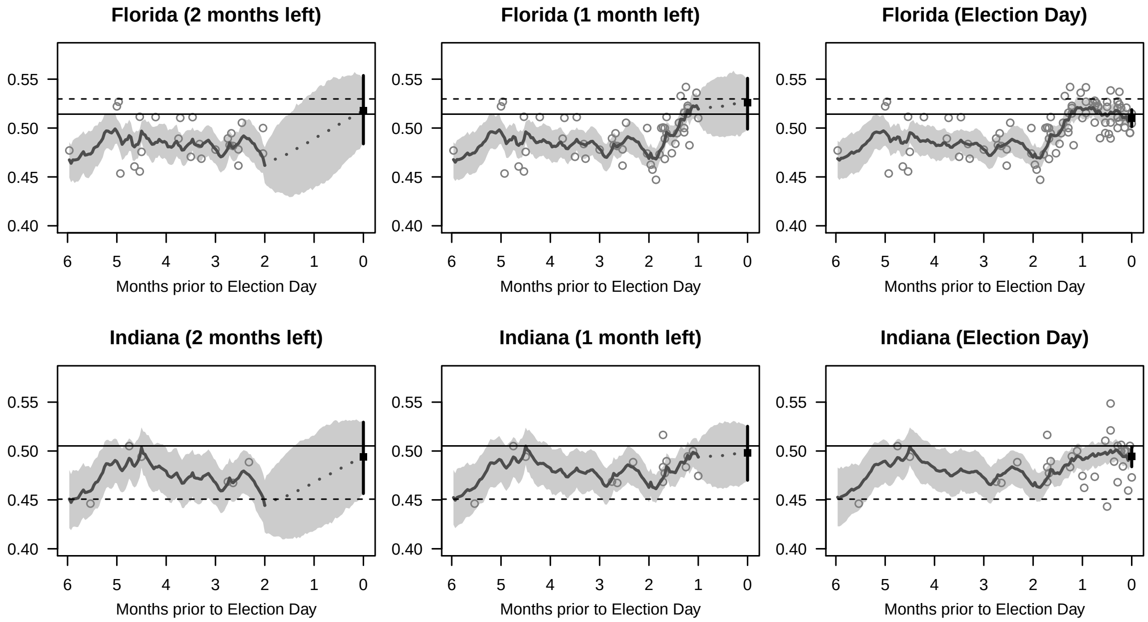

Figure 3: *Forecasting the 2008 presidential election in real time. Results are shown for Florida and Indiana. The vertical axis is the percent supporting Obama; points denote observed poll results. Horizontal lines indicate the late Time-for-Change forecast (dashed) and the actual election outcome (solid). The jagged gray line is the state-level daily estimate of voter preference for Obama,* $\hat{\pi}_{ij}$*. After the final day of polling, these trends project ahead to the Election Day forecast,* $\hat{\pi}_{iJ}$*, plotted as* ■. *Shaded areas, and the vertical bar on Election Day, denote 90% posterior credible intervals.*

of polls were conducted in Florida, Indiana was surveyed only six times between May and August. The early trend estimate in Indiana therefore draws heavily from patterns of public opinion in the other 49 states, illustrating the power of the model to detect subtle campaign effects. The downtick in support for Obama between the two- and three-month mark, for example, coincides with the selection by John McCain of Sarah Palin as his Vice Presidential nominee, and the ensuing Republican National Convention. It is evident that $\hat{\pi}_{ij}$ identifies the central tendency in the polls.

With two months remaining in the campaign, polls in Florida indicated that support for Obama was below both the Time-for-Change forecast and Obama's actual (eventual) vote share. In Indiana, Obama was slightly ahead of the historical forecast, but this was atypical: in most states, as in Florida, fewer voters than expected were reporting a preference for Obama. As a result, estimates of $\hat{\delta}_j < 0$; so after the final day of polling,

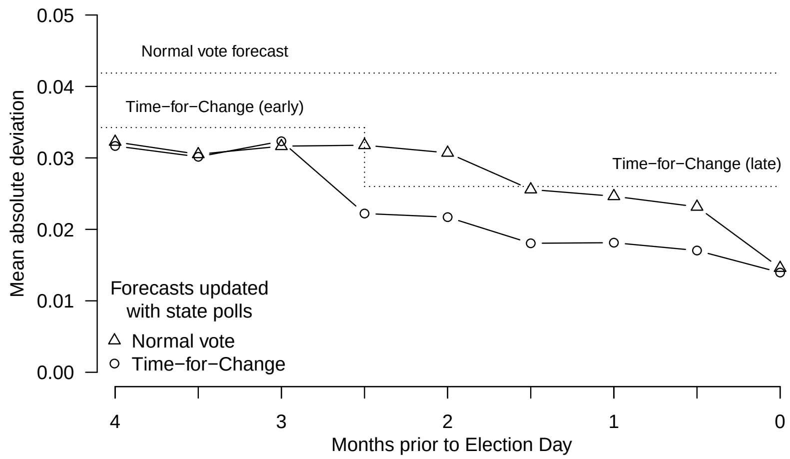

Figure 4: *Sequential reduction in MAD of state-level election forecasts by incorporating trial-heat polls. Dotted lines indicate MAD of baseline structural predictions. Points show forecast MAD, updating from the Time-for-Change and normal vote models. With ten weeks remaining, estimates based on the Time-for-Change model switch from the early to the late forecast.*

$\hat{\pi}_{ij}$ trended upwards to Election Day. In Florida, $\hat{\pi}_{ij}$ moved closer to both the structural forecast and to the actual outcome. In Indiana, $\hat{\pi}_{ij}$ moved away from the structural forecast, but again towards the actual outcome—thus correcting the substantial -5.5% error in the original Time-for-Change forecast.

One month before the election, support for Obama increased nationwide, but the model forecasts remained stable. The 90% HPD interval for the Florida forecast fell from ±3.5% to ±2.6%, and for the Indiana forecast from ±3.6% to ±2.8%. Finally, on Election Day, the model predicted with 90% probability that Obama would win between 50.1% and 51.9% of the major-party vote in Florida, and between 48.4% and 50.5% in Indiana. The actual outcome was 51.4% in Florida and 50.5% in Indiana.

In the complete set of simulations, incorporating polling data into the prior structural forecasts steadily reduces the MAD between state-level election forecasts and the actual outcomes (Figure 4). The largest improvements occur in the final six weeks of the campaign, when the polls become most informative about the election outcome (e.g., Campbell 1996). Yet even polls conducted four months before the election reduce the MAD of the (early) Time-for-Change forecast by 0.3%, and the MAD of the normal vote forecast by 1%. The state-level election forecasts converge in a stable manner towards the election outcomes and are not over-sensitive to short-term changes in current opinion. By Election Day, both sets of forecasts indicate a MAD of 1.4%, with more than half of states (27) predicted to within 1% of the actual result. The largest forecast errors arose in infrequently polled safe states.

Accurate forecasting of vote shares aids in predicting the winner of each state. This is most important in competitive swing states, where the difference of a few percentage points could decide the election. The baseline structural forecast using the Time-for-Change model mispredicted seven states early and four late: Arkansas, Indiana, Missouri, and North Carolina. The normal vote forecast mispredicted nine states. By comparison, the only state incorrectly predicted by the model using trial-heat polls through Election Day was Indiana (Figure 5). Even so, Obama's vote share in Indiana was in the 90% HPD interval of $\hat{\pi}_{iJ}$, as noted.

Estimates of uncertainty in $\hat{\pi}_{iJ}$ enable early identification of states in which the election is likely to be close. I consider a state to be a *swing state* when the posterior probability of a Democratic victory is between 10% and 90%. The number of swing states declined during the campaign, as more information from polls became available (Figure 5). Large states that proved pivotal to Obama's victory—including Florida, Ohio, and Virginia—were already nearly certain to be won by Obama with a month or more remaining. The battleground states of Missouri, Montana, North Carolina, and Indiana were likewise identifiable far in advance of the election. The surprising competitiveness of states such as Arkansas, West Virginia, North Dakota, and Nevada through the final two weeks of the campaign were attributable to a combination of limited polling and late-breaking voter preferences in those states.

Aggregating the state-level forecasts, Obama's predicted electoral vote tally was consistently above the 270 needed to win the presidency (Figure 6). With two months remaining in the campaign, forecasts based on updating the Time-for-Change model predicted

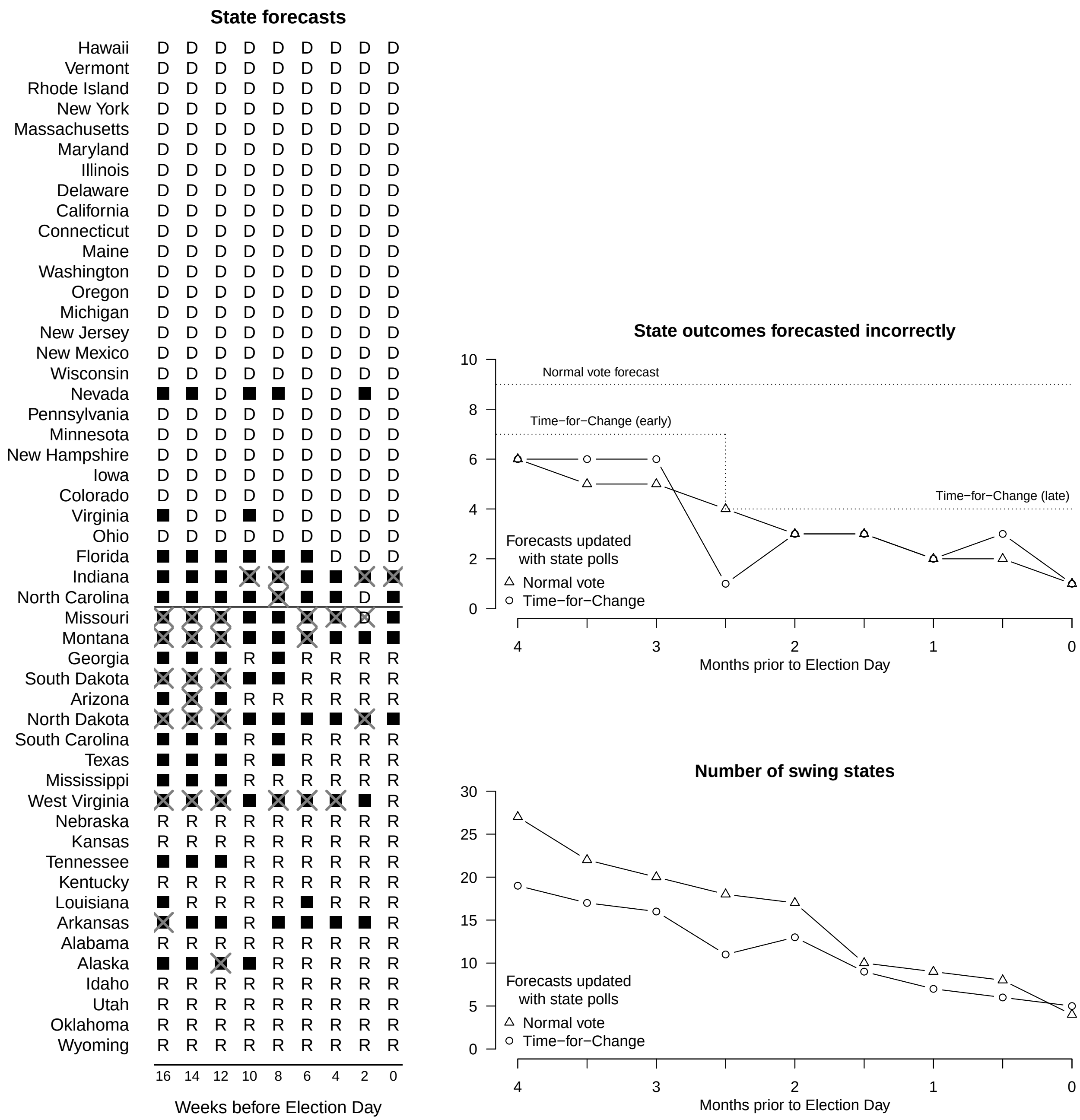

Figure 5: *Swing states and forecast accuracy. Left: Forecasts by updating the Time-for-Change model with pre-election polls;* D *indicates the model forecasted a Democratic victory,* R *indicates the model forecasted a Republican victory. Swing states are denoted as squares. A gray X indicates that the estimated* $\hat{\pi}_{iJ}$ *mispredicted the state winner. States are sorted by Obama's final vote share; Obama won North Carolina (50.2% of the major-party vote), but lost Missouri (49.9%). Right: Total number of swing states and mispredicted state winners during the campaign.*

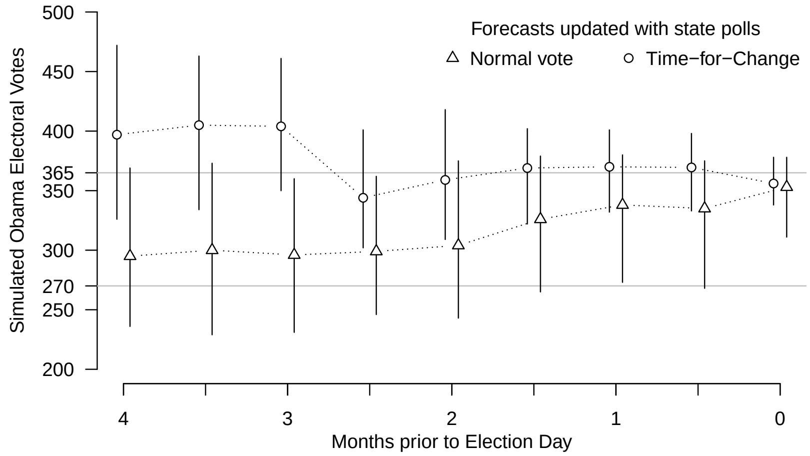

Figure 6: *Distributions of forecasted Obama electoral votes. Vertical bars span 95% of simulated electoral vote forecasts; points denote the median. A majority is 270.*

the final outcome to within six electoral votes, corresponding to a near 100% chance of victory for Obama. On Election Day, the model projected a range of 338 to 387 Obama electoral votes, with 95% probability. Obama actually won 365 electoral votes, which (in a historical anomaly) included the single electoral vote of Nebraska's 2nd Congressional District. Forecasts based on updating the normal vote model gave Obama an 87% chance of winning with two months remaining, and 100% on Election Day, with between 311 and 378 electoral votes.

Combining a well-motivated structural forecast with information from large numbers of pre-election polls thus generates early and accurate predictions of the presidential election outcome. Updating continually during the campaign also improves the precision of the forecasts. For comparison, the range of Obama electoral votes predicted by Lock and Gelman (2010), who updated a prior structural forecast made close to Election Day using only one set of state-level pre-election polls conducted nine months before the election, was between 250 and 450. In their simulations, Obama had a 99.9% chance of victory, but this high level of certainty was only achievable because Obama won by a relatively large margin in 2008. In a closer election, much greater precision would be required to predict the winner with confidence.

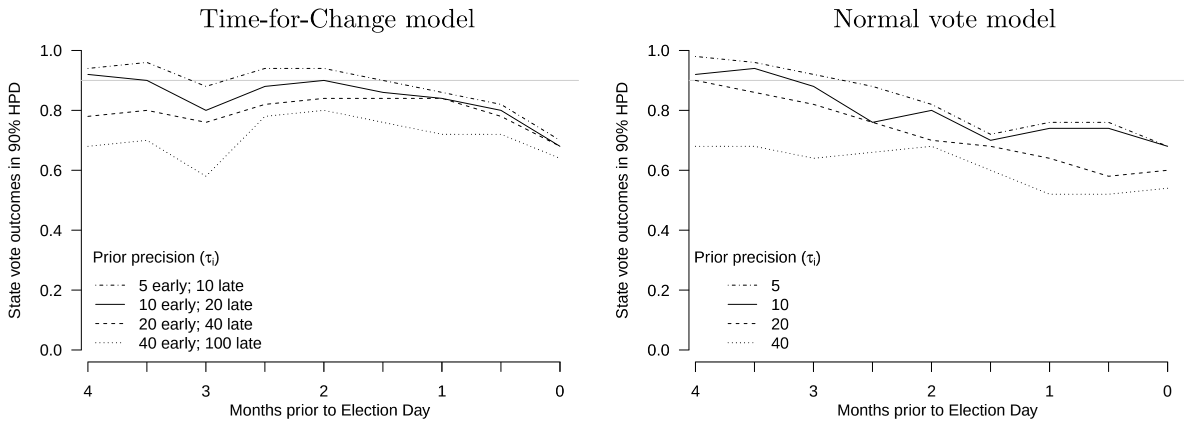

Figure 7: *Coverage of nominal 90% posterior credible intervals around $\hat{\pi}_{iJ}$ for choices of prior precision τ_i. Solid lines correspond to the τ_i used in the above simulation.*

4.4 Prior Sensitivity Analysis

The choice of τ_i (Equation 3) indicates the analyst's prior certainty in the structural model forecasts h_i, before information from state-level polls is considered. Although the τ_i are meant to specify an informative prior, their selection is not arbitrary. If τ_i is very high, the vote forecasts $\hat{\pi}_{iJ}$ will not update from trial-heat polls until just before Election Day. Large values of τ_i will also reduce the posterior uncertainty in $\hat{\pi}_{iJ}$, which can lead to errors in both the identification of swing states, and the estimation of the probability of winning each state and the presidency. Depending on τ_i, the posterior HPD intervals for $\hat{\pi}_{iJ}$ should be wide enough to include the actual election outcomes in the expected proportion of states.

I calculate the coverage rate of the nominal 90% Bayesian posterior credible intervals for $\hat{\pi}_{iJ}$, at various values of τ_i (Figure 7). Updating from the Time-for-Change model, setting $\tau_i = 10$ early, and $\tau_i = 20$ late, produces 90% credible intervals for $\hat{\pi}_{iJ}$ that include the election outcomes in between 80% and 90% of states through the final two weeks of the campaign. This coverage is achieved despite the overconfidence expected in estimates of $\hat{\pi}_{iJ}$ due to house effects and other sources of non-sampling error. Coverage is somewhat worse under the normal vote model. Values of $\tau_i > 20$ generate credible intervals that are misleadingly narrow.

As Election Day nears, the proportion of states in which the election outcome is forecasted within the posterior 90% HPD interval of $\hat{\pi}_{iJ}$ falls below 80%. However, this is primarily a function of limitations and anomalies in the underlying survey data, rather than the choice of τ_i. Forecast intervals for $\hat{\pi}_{iJ}$ are least accurate in states with limited numbers of polls, which prevents averaging to reduce error. Because states that are polled infrequently also tend to be uncompetitive, there is very little practical consequence to the narrower than expected forecast intervals in these states. Indeed, in the earlier simulation, only one forecast error occurred in a state not considered a swing state at the time; Missouri, with 2 weeks remaining (Figure 5).

4.5 Trends in Voter Preferences during the Campaign

Looking back from Election Day, past estimates of $\hat{\pi}_{ij}$, $\hat{\beta}_{it[j]}$, and $\hat{\delta}_j$ reveal how voter preferences evolved during the campaign. In 2008, the opinions that voters held about the presidential candidates changed very gradually over time, compared to the large fluctuations in the polls. The state with the most consistent attitudes was Wyoming, where $\hat{\pi}_{ij}$ varied within a range of just 4.6% over the final six months of the campaign. Preferences in Alaska were the most variable; there, $\hat{\pi}_{ij}$ ranged 10% from its lowest to its highest point. Among all states' daily changes in $\hat{\pi}_{ij}$, 98% were by less than 0.5%. In a typical state, the variance in the poll results was three to five times greater than the variance in $\hat{\pi}_{ij}$. This suggests that the combined error in pre-election polls due to sampling variability and house effects may be even greater than what was estimated by Erikson and Wlezien (1999) and Wlezien and Erikson (2002).

Most of the temporal variation in state-level opinion was due to national-level campaign effects (Figure 8). Estimates of $\hat{\delta}_j < 0$ reflect the fact that Obama ran behind his eventual election performance in most states for most of the campaign. Once the common effects of $\hat{\delta}_j$ are filtered away, the unique state effects $\hat{\beta}_{it[j]}$ demonstrate relative stability. Where trends in $\hat{\beta}_{it[j]}$ do occur, they tend to happen in one sustained direction. The

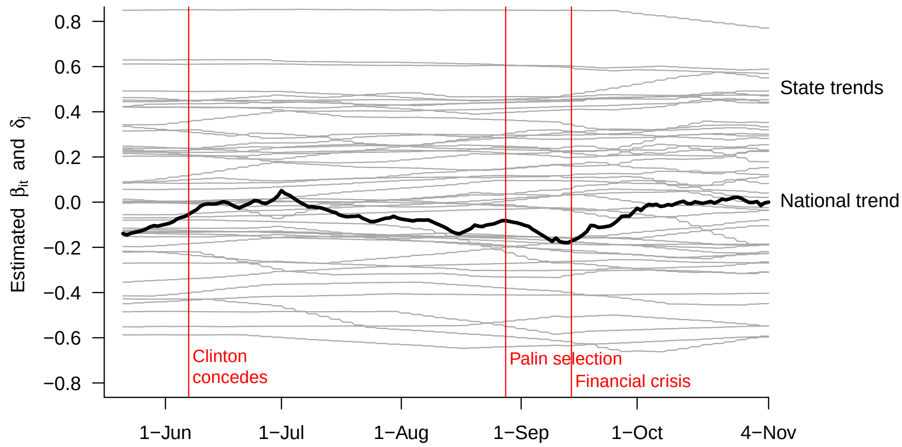

Figure 8: *After the election: Past state-level trends in $\hat{\beta}_{it[j]}$ (gray), and the common trend in $\hat{\delta}_j$ (black), during the campaign. Some of the most significant short-term changes in $\hat{\delta}_j$ coincide with major campaign events. Estimates of $\hat{\delta}_j$ and $\hat{\beta}_{it[j]}$ exhibit the same historical trends whether the structural forecast is based on the Time-for-Change model (shown) or the normal vote model.*

national-level effects evened out approximately four weeks before the election. At that point, voter preferences within individual states began to move towards the final outcome in divergent, state-specific directions.

5 Discussion

The trend towards increased pre-election polling—especially at the state level—appears likely to continue in the 2012 presidential campaign, and beyond. Public opinion polls have become integral to political reporting, and interest in following the "state of the race" only seems to grow each year. For analysts, the availability of these survey data creates new opportunities for statistical models that can apply theories of mass opinion formation and voter behavior to produce better estimates of voter preferences during the campaign, as well as forecasts of the outcome on Election Day.

This paper has presented a dynamic Bayesian statistical procedure for processing and interpreting the results of state-level pre-election opinion polls in real time. Applied to the 2008 presidential election, the model generated a nearly perfect prediction of which states would be won by Barack Obama and John McCain, and by how much; and estimated with certainty that Obama would win the presidency. The model also produced daily estimates of state-level opinion during the campaign and reliably predicted which states would be most competitive on Election Day.

The results of my analysis highlight a number of lessons about presidential campaigns and elections. First, presidential election forecasts can, and should, be made at the state level. State-level outcomes can be predicted accurately and reliably by combining readily available historical and public opinion data. Furthermore, these forecasts need not be overly sensitive to short-term fluctuations in voter preferences during the campaign. Most of the variation in pre-election polls is due to sampling variability. But even after averaging this away, much of the remaining day-to-day variation in state-level opinion is attributable to national-level campaign effects. By smoothing and filtering the trial-heat polling data, it is possible to produce election forecasts that converge towards the outcome in a gradual and stable manner. During the campaign, any report suggesting that voter preferences have changed by more than a few tenths of a percent on a daily basis should be treated with suspicion.

There nevertheless remain inherent limitations to what can be learned from state-level public opinion data—no matter how many surveys are released in the next election cycle. With current numbers of polls, it is relatively easy to forecast the outcomes of state-level presidential elections on the eve of the election, as I have shown. The challenge remains to produce accurate forecasts many months in advance. My solution seeks to combine the best features of structural forecasts and pre-election polls, downweighting the historical forecasts over time in favor of the information contained in more recent survey data. But even so, the biggest forecasting improvements only occur one or two months in advance of the election. This is not because there is not *enough* polling data, but because the polling data themselves are noisy and, far before Election Day, subject to inaccuracies. Future research into presidential campaign dynamics may yet discover new ways to extract meaning from those early polls.

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