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Forecasting presidential elections using history and polls

Lloyd B. Brown[a], Henry W. Chappell Jr.[b,*]

[a]*Department of Economics, College of Charleston, Charleston, SC 29424, USA*
[b]*Department of Economics, University of South Carolina, Columbia, SC 29223, USA*

Abstract

We develop a method for efficiently using current poll data to update election forecasts based on historical relationships. The method is applied on an *ex post* basis to forecast Republican and Democratic shares of the national vote in U.S. Presidential elections from 1952 to 1992. Using poll data substantially improves the performance of forecasting models that rely solely on historical fundamentals. Moreover, when poll data are used appropriately, their information content dominates in the calculation of an optimal forecast. The method has also been applied on an *ex ante* basis to forecast the 1996 presidential election, producing a series of highly accurate predictions over the 2 month period before the election.

Keywords: Election forecasting; Polls; Presidential elections

1. Introduction

In a recent paper, Gelman and King (1993) (pp. 409–410) suggest that the attention given to the ''horserace'' aspects of presidential elections is misplaced. They report that:

> For some time now, political scientists have forecast the outcome of presidential elections accurately using only information available before the start of the general election campaign. However, the numerous ''trial heat'' public opinion surveys (polls about whether likely voters plan to cast their ballots for the Democratic or Republican candidate for president) conducted during the campaign vary enormously in support for the Democratic and Republican candidates. At one point during the general election campaign, survey respondents favored Dukakis over Bush by 17 percentage points, and yet any reasonable application of the political science literature would have made George Bush almost certain to win the November election.

Gelman and King argue that trial heat polls reflect ephemeral responses to daily campaign events which eventually have little impact on election outcomes. Given data on election fundamentals, poll data are at best redundant, and might even be misleading for forecasting purposes.[1]

*Corresponding author. Tel.: +1-803-7777400; fax: +1-803-7776876.

[1]Gelman and King also note that polls converge to the eventual voting outcome just before the election. They argue that voters rationally seek out information in the last few days of the campaign and then make up their minds. The information they find may have been available much earlier, enabling analysts to predict their ultimate decisions accurately, even if polls could not. Hence, fundamentals predict elections well, while early polls do not.

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The work of Lewis-Beck and Rice (1984); Campbell and Wink (1990); Campbell (1996) provides a somewhat different view. Campbell and Wink agree that elections can be accurately predicted by early September in the general election campaign, but they employ a trial heat poll as an essential input in making a forecast.[2] As their work demonstrates, poll results may not be accurate as literal forecasts, but they are useful predictors of election outcomes in a statistical context.[3] Erikson and Wlezien (1996); Wlezien and Erikson (1996) also present evidence confirming the usefulness of poll data. Their results show that approval ratings and trial heat polls capture the non-economic dimensions of incumbent performance that are relevant for electoral choices.[4]

Some models, in particular those of (Fair, 1978, 1982, 1988, 1996), eschew the use of polls in explaining the Presidential vote. Although these models focus on explaining the ''fundamental'' determinants of election outcomes, they have also been used for forecasting. The 1992 election demonstrates the perils of ignoring polls in election forecasting, however. Fair's model predicted a comfortable Bush victory, even as post-convention polls made it clear that his re-election was doubtful. Fair's forecast ultimately erred by 9 percentage points. In retrospect one might argue that Fair's model was intrinsically misspecified, but this was not obvious prior to 1992.

In this paper we develop an election forecasting method that generalizes and extends previous analyses. Our method uses both poll data and historical relationships to produce its forecasts. A key feature of our approach is that it permits poll data to be assimilated in an optimal and timely manner. New polls can immediately be used to update an earlier forecast in Bayesian fashion. Although previous studies have considered how the timing of a poll affects its usefulness in forecasting, in developing our method we address this issue in a more formal manner.[5]

In Section 2 of the paper we describe the theoretical underpinnings of the forecasting method. Section 3 describes an ex post application of the method for forecasting national vote shares in presidential elections from 1952–1992. In Section 4, we describe similar forecasts for the 1996 election which were made on an ex ante basis as the campaign proceeded. Conclusions follow in Section 5.

2. An expository model

This section describes a method for combining historical data and a pre-election poll in order to forecast an election outcome. We begin by specifying the processes determining election outcomes and relating those outcomes to a pre-election poll.

The process determining votes is described by Eq. (1):

$$V(t) = \boldsymbol{x}(t)\boldsymbol{\beta} + \varepsilon(t), \; t = 1, \ldots, T \tag{1}$$

In this equation $V(t)$ is the Democratic percentage of the national two-party vote in election t and $\mathbf{x}(t)$ and $\boldsymbol{\beta}$ are vectors of exogenous variables and parameters. We assume that $\varepsilon(t)$ is a normally distributed random error with mean 0 and constant variance σ^2_ε, and that it is uncorrelated with $\mathbf{x}(t)$. Eq. (1) is best thought of as a model like Fair's, in which voting outcomes are related to their fundamental historical determinants.

Now suppose that a single pre-election trial heat

[2]Campbell (1996) has argued that, as a practical matter, updating forecasts based on the most recent polls has not provided substantial gains. Over the eleven elections from 1952 to 1992, early September polls produced forecasts which were about as accurate as those produced using polls conducted later in the campaign.

[3]Even Gelman and King apparently use an early campaign trial heat poll as a regressor in their own forecasting equation. Although they do not explicitly report their complete model specification in their paper, they describe it as equivalent to Campbell (1992) model, with several variables added. Campbell included the September trial heat poll as an explanatory variable in his model.

[4]Other presidential forecasting models are described in Abramowitz (1996); Campbell (1992); Holbrook (1996); Lewis-Beck and Tien (1996); Norpoth (1996); Rosenstone (1983).

[5]Campbell (1996); Campbell and Wink (1990) and Wlezien and Erikson (1996) have estimated separate forecasting equations for use with polls obtained at specific dates prior to the election, i.e. early September, mid-September, early October, etc. Erikson and Sigelman (1990) have employed similar models to forecast party vote shares in congressional elections. These models do not directly produce forecasts at arbitrary dates before the election, however.

poll is administered. The poll results are assumed to be related to subsequent voting outcomes by:

$$V(t) = \alpha_0 + \alpha_1 S(t) + \mu(t). \tag{2}$$

In this equation, $S(t)$ is the percentage of survey respondents (who report a preference for one of the two major parties) who favor the Democratic candidate in election t, and α_0 and α_1 are constant parameters. The poll is assumed to be subject to random sampling and response errors, which are together included in the error term $\mu(t)$. We initially assume that $\mu(t)$ is normally distributed with mean 0 and constant variance σ^2_μ, and that it is uncorrelated with $S(t)$.

Some analysts treat polls as literal forecasts. In doing so, they implicitly assume that $\alpha_0 = 0$, that $\alpha_1 = 1$, and that σ^2_μ reflects only sampling error. These conditions would hold if the poll sample were representative of the eventual voters, if all responses were truthful, if votes and polls were accurately counted, and if voters never changed their minds between the poll date and election day. Since these circumstances are unlikely to hold, it is inappropriate to impose the indicated parameter restrictions. Suppose, for example, that an early poll shows that 60% of all respondents favor candidate A, while 40% favor candidate B. Furthermore, suppose that at a given polling date supporters of either candidate are equally likely to change their minds, and that 20% of all voters typically do so before the election. Under these assumptions the expected voting outcome is 56% for candidate A and 44% for candidate B, and the appropriate forecasting equation would have $\alpha_0 > 0$ and $\alpha_1 < 1$.[6] Other response biases could also affect the values of these parameters.

Our problem is to use empirical versions of Eqs. (1) and (2) to create forecasts of the upcoming vote, $V(T+1)$. We first consider a forecast based upon fundamental historical determinants of the vote, obtained from Eq. (1). To estimate this equation we use time series data over elections, obtaining estimates of $\boldsymbol{\beta}$ and σ^2_ε, denoted $\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}^2_\varepsilon$. We then calculate a forecast, $\hat{V}_\mathrm{h}(T+1) = \mathbf{x}(T+1)\hat{\boldsymbol{\beta}}$ (where the subscript "h" indicates a forecast based on the "historical" regression relationship). The forecast error is defined as $e(T+1) = V(T+1) - \hat{V}_\mathrm{h}(T+1)$ and its estimated variance, $\hat{\sigma}^2_e$, is easily calculated with regression output.[7]

We then estimate Eq. (2) in a similar fashion and produce an alternative forecast, $\hat{V}_\mathrm{s}(T+1) = \hat{\alpha}_0 + \hat{\alpha}_1 S(t)$ (the subscript "s" refers to the forecast made on the basis of survey data). We denote the prediction error for the poll forecast as $u(T+1)$, where $u(T+1) = V(T+1) - \hat{V}_s(T+1)$. An estimate of its variance, $\hat{\sigma}^2_u$ is again easily calculated.

During the election campaign, suppose that an initial forecast is made on the basis of the historic regression relationship. However, as the campaign proceeds and poll results become available, the initial forecast should be updated. For example, in 1992 successive polls made it increasingly clear that Fair's early prediction was errant, and this information could have been used to produce a more accurate revised forecast. To forecast the upcoming vote optimally using both historic information and a polling outcome, we invoke the solution to a Bayesian updating problem. Given variances for the two forecast errors, $e(T+1)$ and $u(T+1)$, an appropriate forecast is given by the expected value of the posterior distribution for $V(T+1)$:[8]

$$\hat{V}(T+1) = \frac{\sigma^2_e(T+1)}{\sigma^2_e(T+1) + \sigma^2_u(T+1)}\,\hat{V}_\mathrm{s}(T+1) + \frac{\sigma^2_u(T+1)}{\sigma^2_e(T+1) + \sigma^2_u(T+1)}\,\hat{V}_h(T+1) \tag{3}$$

Although the true variances in Eq. (3) are not

[6] Campbell (1996); Campbell and Wink (1990) find that $\alpha_0 > 0$ and $\alpha_1 < 1$ for polls at various pre-election dates. Our own data also reject the restrictions $\alpha_0 = 0$ and $\alpha_1 = 1$.

[7] The estimated variance is given by:

$$\hat{\sigma}^2_e(T+1) = \hat{\sigma}^2_\varepsilon + \mathbf{x}(T+1)'\{\hat{\sigma}^2_\varepsilon[\mathbf{X}'\mathbf{X}]^{-1}\}\mathbf{x}(T+1).$$

where $\mathbf{X}$ is a $T \times k$ data matrix.

[8] We follow the analysis of Judge et al., 1988 (120–125), who describe updating the estimate of the mean of a normally distributed random variable. Both $e(t)$ and $u(t)$ are approximately normally distributed, with the approximation improving with larger sample sizes.

known, a forecast can be made employing estimated variances in their places.[9]

An intuitive interpretation for the result provided in Eq. (3) is straightforward. The appropriate vote share forecast, $\hat{V}(T+1)$ is a weighted average of the poll regression forecast, $\hat{V}_s(T+1)$, and the historical fundamentals regression forecast, $\hat{V}_h(T+1)$. The relative weight attached to each forecast is larger when its associated forecast error is smaller.

In our empirical work, the approach outlined above is generalized in two ways. First, the specification of Eq. (2) is modified to permit the parameters α_0 and α_1 to vary with time between the poll and the election. Second, we relax the assumption of a constant variance, and instead permit the variance to depend on the interval between the poll and the election. In addition, the last poll before an election is usually based on a larger sample, which should further reduce sampling error.[10] We therefore allow the variance for final polls to differ from others.

3. Forecasting national voting outcomes: 1952–1992

We first describe the empirical specification for Eq. (1) and report regression estimates using nationally aggregated presidential election data. Our empirical specification is given by the following simple equation:

$$V(t) = \beta_0 + \beta_1 \,\Delta Y(t)I(t) + \varepsilon(t) \tag{1'}$$

where $V(t)$ is the Democratic share of the two-party vote, $\Delta Y(t)$ is the annualized growth rate of GDP in the first two quarters of the election year, and $I(t)$ is a dummy variable equal to 1 if the incumbent president is a Democrat and equal to -1 if he is Republican. If β_1 is positive, the equation implies that economic growth improves the electoral chances of the incumbent party.

The literature on aggregate voting outcomes in presidential elections clearly supports the hypothesis that growth favors incumbents. Fair (1988) finds that growth in the second and third quarters of the election year provides the best fit, but third quarter growth is not observed until the election campaign is well underway. Since our focus is on forecasting, we have used the first two quarters of growth in our equation.

Fair included other variables in his equation, but found only modest evidence of impacts on voting. Among these variables were a measure of inflation, a dummy variable to indicate whether a candidate was an incumbent running for reelection, and a time trend. Our own estimation using the 1952–1992 sample of elections (in contrast to the 1916–1984 sample period employed by Fair) finds no significant effects for these variables. Our final specification therefore includes only a constant term and an economic growth variable. In Table 1, the results show that real GDP growth is statistically significant and has a estimated coefficient of 0.83, a value comparable to previous estimates.

We next consider the estimation of a generalized version of Eq. (2), which relates voting outcomes to pre-election polls. As we have noted, parameters of the equation are now permitted to vary with the interval between the poll and the election, and the error term is assumed to be heteroscedastic. In addition, we now explicitly recognize that there are multiple polls for each election, with polls in election t indexed by $i=1, \ldots, N(t)$. Eq. (2) is reformulated as:

$$V(t) = \alpha_0 + \alpha_1 \mathrm{DBE}(i,t) + [\alpha_2 + \alpha_3 \mathrm{DBE}(i,t)]S(i,t) + \mu(i,t), \tag{2'}$$

where DBE(i, t) is the length of the interval between

Table 1
Economic growth and presidential elections, 1952–1992; dependent variable: share of the two-party vote for the democratic candidate

Variable	Parameter	Description	Coefficient	t-statistic
CONSTANT	β_0	Constant	48.88	31.66
$\Delta Y(t)I(t)$	β_1	GDP growth	0.83	2.60
$\bar{R}^2$			0.40	

[9] It is also possible to estimate the variance of $\hat{V}(T+1)$ using the variance of the posterior distribution, which is given by:

$$\sigma^2_{\hat{V}}(T+1) = \frac{\sigma^2_e(T+1)\sigma^2_u(T+1)}{\sigma^2_e(T+1) + \sigma^2_u(T+1)}.$$

[10] Sample sizes were not always reported, but those reported were usually around 1200. Sample sizes for final polls were usually about 2000.

Table 2
Polls and presidential elections, 1952–1992; dependent variable: share of the two-party vote for the democratic candidate

Variable	Parameter	Description	Coefficient	t-statistic
Regression coefficients				
CONSTANT	α_0	Constant	8.96	3.80
DBE(t)	α_1	Days before election	0.18	4.72
$S(i,t)$	α_2	Democratic poll share	0.81	16.85
$S(i,t)\times$DBE(i,t)	α_3	Interaction	−0.0040	5.28
Heteroscedasticity process				
CONSTANT	γ_0	Constant	2.50	6.84
DBE(i,t)	γ_1	Days before election	0.0041	0.78
FINAL(i,t)	γ_2	Final poll dummy	−0.97	1.95
$\bar{R}^2$			0.77	

the poll date and the day of the election (''days before election'') for poll i in year t.

To permit a heteroscedastic error term, we specify that the standard deviation of $\mu(i, t)$ is given by:

$$\sigma_\mu(i, t) = \gamma_0 + \gamma_1 \mathrm{DBE}(i, t) + \gamma_2 \mathrm{FINAL}(i, t), \qquad (4)$$

where FINAL(i, t) is a dummy variable equal to 1 if the ith poll in election year t is the final pre-election poll.

We have jointly estimated the parameters of Eqs. (2′) and (4) using a sample of 101 trial heat Gallup polls explaining presidential election outcomes from 1952 to 1992.[11] The numbers of polls vary somewhat from election to election, as do poll dates. Maximum likelihood estimation was employed for this equation because of the non-standard specification of the heteroscedastic error. Results are provided in Table 2.

The results are generally consistent with our expectations. In particular, the estimate of α_1 is positive and that of α_3 negative, and each is significantly different from zero. These results indicate that the coefficient on the poll is larger and the constant term lower for polls closer to the election. Similar coefficient patterns have been found by Campbell and Wink (1990); Campbell (1996). The results also reveal a tendency for polls to overstate support for Democratic candidates. For example, if polls show support equally divided between Republicans and Democrats 30 days before the election, our equation predicts a Republican victory by a 51.5% to 48.5% margin. Table 3 provides additional details on this bias.

Estimates of the parameters of the heteroscedasticity process are reported in Table 2. There is only weak evidence of heteroscedasticity related to DBE, but the coefficient of FINAL is negative and significant, as hypothesized.

The final step in our procedure involves calculating a weighted average forecast based on both poll and regression information, as described in Eq. (3). We have calculated forecasts at each polling date for elections from 1952 to 1992. To calculate forecasts in year t, we used data from all years in the sample except year t in the estimation stage. For example, to produce a forecast in 1964, we estimated Eq. (4) and equation (5) excluding observations from 1964, but using other available data from 1948 to 1992. By excluding 1964 data we avoid biases that might result from using knowledge about that particular year's election outcome.

To evaluate our forecasting procedure, we have

Table 3
Best election forecasts for selected poll results

Selected Democratic poll percentages	Days before 1992 election			
	3	30	60	90
40	41.1	41.6	42.1	42.7
45	45.1	45.0	45.0	44.9
50	49.1	48.5	47.8	47.0
55	53.1	51.9	50.6	49.2
60	57.1	55.4	53.4	51.4

[11] The poll data were extracted from various issues of the *Gallup Political Index* and the *Gallup Poll*.

Table 4
Mean-squared forecast errors, national vote, various forecasts: 1952–1992

	Unadjusted polls	Adjusted polls	Historical fundamentals	Optimal mix
Mean-squared errors for:				
Final poll	3.5	3.0	36.9	3.5
Polls nearest 30 DBE	22.4	12.0	36.9	11.1
Polls nearest 60 DBE	24.8	8.4	36.9	8.7
Polls nearest 90 DBE	40.9	13.6	36.9	13.0

calculated mean-squared forecast errors for our method, and also for forecasts based on poll data alone and on the historical fundamentals alone. Two poll forecasts are reported: an unadjusted ‘‘literal’’ poll forecast and a ‘‘bias-adjusted’’ forecast. The latter is calculated as the prediction from Eq. (2′). Table 4 provides mean-squared errors for forecasts using (i) polls closest to 90 days before each of the 11 elections, (ii) polls closest to 60 days before the election, (iii) polls closest to 30 days before the election, and (iv) polls closest to the day of the election.

These results illustrate the gains from using polls to augment historical regression data. Over the entire sample of poll dates the weighted average forecast has a much lower mean squared error than the historical fundamentals regression forecast. Not surprisingly, economic growth alone cannot fully explain election outcomes and polls appear to capture many of the other influences that matter.

One would expect forecasting accuracy to be improved with proximity to the election, but our results do not provide strong evidence that this is the case. Having final poll data on the eve of the election permits better forecasts, but at 30, 60, and 90 days before the election, forecast accuracy is roughly constant.

Perhaps more surprisingly, bias-adjusted forecasts based on poll information alone appear to forecast as well as our ‘‘optimal’’ weighted average forecast. Apparently polls capture much of information provided by the economic growth variable, even at a horizon of 90 days before the elections. In contrast, Campbell (1996); Campbell and Wink (1990) find that forecasts from regressions including both economic growth and poll outcomes perform better than those based on poll data alone.

The results confirm Campbell’s and Gelman and King’s findings that early polls are not accurate as literal forecasts; but they also show that regressions based on early polls can forecast quite well. Remarkably, if we use Eq. (2′) to forecast the 1988 election just after the Democratic convention when the Dukakis ‘‘lead’’ was 17 points, we forecast a Bush victory by 2 points.

4. Forecasting the 1996 election

We next describe our ex ante forecasts of the 1996 election. During September, October, and November of 1996 these forecasts were posted on our World Wide Web ‘‘Presidential Election Forecasts’’ site at the University of South Carolina.

One change was made to the basic model prior to forecasting in 1996. In our previous analysis, DBE measured the number of days between the poll date and election day. In our analysis for 1996, DBE was truncated so that it was equal to the lesser of 90 or the number of days between the poll date and election day. This change reflected concern about the plausibility of assuming linear DBE effects long before the election.[12] We also regularly reported an alternative forecast that employed a slightly different specification for Eq. (1′), the equation relating voting outcomes to historical variables. This specification added to the model a dummy variable indicating a candidate who was a ‘‘Southern Democrat’’. In fact, Democratic candidates who were Southerners were particularly successful during the 1952–1992 period. Although the predictive power of this variable might be coincidental, it has some

[12]This change in specification has only minor effects on estimates of the model parameters. Furthermore, all forecasts generated for 1996 used polls with horizons of less than 90 days.

theoretical appeal as an indicator of Democrats who might be viewed as moderates rather than liberals.

Beginning in early September, we used Eq. (3) to calculate ''optimal'' forecasts of the Democratic share of the two-party vote on a weekly basis. Data from 1952–1992 were used to estimate Eqs. (1′) and (2′), the primary forecasting equations. For each forecast, we employed the most recent Gallup poll and the most recent estimate of first and second quarter real GDP growth as independent variables.

The series of forecasts is graphically portrayed in Fig. 1, which also plots unadjusted Gallup polls and the final election outcome. The Brown-Chappell forecast plotted in the figure is the one generated by the original version of the model, which excludes the Southern Democrat dummy (with the Southern Democrat dummy the forecast was actually slightly more accurate). As the Figure illustrates, early in the campaign, Clinton's ''lead'' in the polls was large. However, because early leads (especially those held by Democrats) tend to dissipate, our early forecasts of the Clinton vote share were much lower. For example, in mid-September the polls showed Clinton with 62% of the two-party vote, while our model predicted that he would ultimately win with 54%. Although our weekly forecasts moved in response to new poll information, that response was muted. Furthermore, as the election approached, our forecast method attached greater weight to the poll numbers and the gap between the poll and our forecast narrowed.

Fig. 1 illustrates that our forecast was consistently between 52% and 56% over the pre-election period. Our final forecast, issued on the morning of the election and based on election eve poll data, predicted a Clinton share of 53.9%. Our alternative forecast, which accounted for the historical advantages of Southern Democrats, predicted a Clinton share of 54.3%. Clinton actually received 54.7% of the two-party vote. The unadjusted final Gallup poll predicted 55.9% for Clinton and it had predicted 59.3% just a week before the election.

5. Conclusions

We have developed a method for using both poll data and historical relationships to forecast presidential elections. By treating forecasting as a Bayesian updating problem, we are able to produce continuously revised forecasts as new poll data are released in the course of a campaign. In our forecasts, the optimal weights attached to polls and historical information vary with the time between the poll and the election.

In practice, the pattern of weights produced by our method is similar to the pattern revealed in regressions reported by Campbell and Wink (1990);

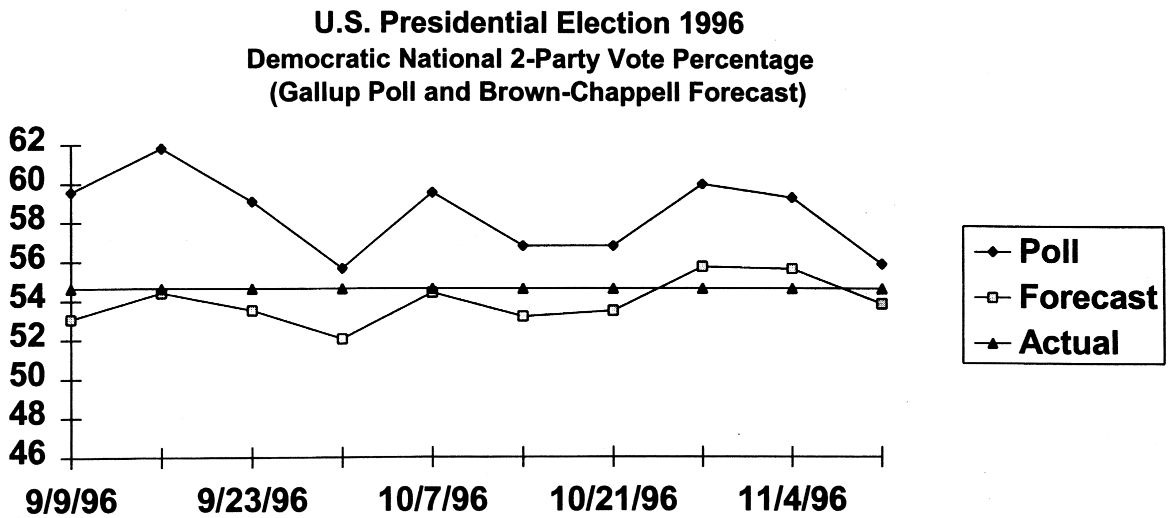

Fig. 1. Polls, forecasts, and the actual election outcome.

Campbell (1996); polls receive increasing weight as the election approaches. Our results show that forecasts using poll data outperform those based on historical relationships alone, but forecasts based on poll data alone are comparable in accuracy to those which combine poll data and economic performance measures. Excepting final polls, there is little indication that forecasts made closer to election day are much more accurate than those made 60 or 90 days earlier. This finding is consistent with earlier research. Thus, while we would advocate using the most recent polls available when forecasting, our recommendation rests more on logic and prior beliefs than on a statistical demonstration.

Our method was used to produce a series of ex ante forecasts during the 1996 campaign. These forecasts were consistently accurate in the two months preceding the election, and generally compared favorably with a compendium of forecasts presented by other analysts before the election.[13]

Since our method is in many respects similar to those employed by others, notably Campbell and Wink (1990); Campbell (1996), we should note several differences. Campbell and Wink's method is to regress vote outcomes on an economic growth measure and a poll outcome. Separate regressions are estimated for specified poll dates, permitting one to make forecasts at those dates during the campaign. In contrast, our estimation procedure permits continuously varying parameter estimates. With this method one can make a forecast at any date prior to the election, whenever new poll data arrives. Our method also permits the use of all pre-election poll observations in the estimation stage, while Campbell and Wink discard data points where a poll is not closest to one of their pre-specified dates. A potential drawback of our procedure, at least as implemented here, is that it imposes some ''smoothness'' on the pattern of weights used in forecasting. Campbell and Wink essentially let the data speak for themselves on this issue, while estimating a larger number of parameters over multiple equations. In the future, we plan to modify our specification of Eq. (2′) to permit a more flexible pattern of time-varying weights, while still employing our basic method.

[13]See the ''Presidential Vote Forecast Compendium'' in the October 1996 issue of *American Politics Quarterly*. In fairness, we note that most of these forecasts were issued before September.

A second task for the future involves adapting our method to forecast state-specific election outcomes. State outcomes in presidential elections are of obvious importance given that winning candidates are selected in the Electoral College. Campbell (1992); Gelman and King (1993); Rosenstone (1983) have previously developed state-specific election forecasting models, but these models have not used state-specific poll data. Data limitations probably explain this omission. Although historical data related to state voting outcomes are available over many past elections, state-specific polls have been widely reported only since 1988. Our method could be particularly useful in these circumstances, since it does not require identical sample periods for the equations producing poll-based and history-based forecasts. Furthermore, given the overall paucity and irregular timing of state-specific polls, it would be desirable to adopt a method that can use all available data points and can forecast at arbitrary pre-election dates.

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Biographies: Henry W. CHAPPELL, Jr., is Professor of Economics at the University of South Carolina, where he teaches courses in macroeconomic theory, microeconomic theory, and industrial organization. He has published widely on topics relating politics and macroeconomic policymaking, and most recently has studied voting on monetary policy decisions in the Federal Open Market Committee at the Federal Reserve.

Lloyd BROWN is currently teaching for the Economics Department at the University of Charleston. He teaches courses in Economic History and International Trade. His research interests include election forecasting and environmental damage assessment. He also writes customized database software for business and industry.