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# A New Approach to Estimating the Probability of Winning the Presidency

Edward H. Kaplan\* and Arnold Barnett†

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## Abstract

As the 2000 election so vividly showed, it is Electoral College standings rather than national popular votes that determine who becomes President. But current pre-election polls focus almost exclusively on the popular vote. Here we present a method by which pollsters can achieve both point estimates and margins of error for a presidential candidate's electoral-vote total. We use data from both the 2000 and

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1988 elections to illustrate the approach. Moreover, we indicate that the sample sizes needed for reliable inferences are similar to those now used in popular-vote polling.

## 1 Introduction

National opinion polls about US presidential races generally focus on candidate standings in the popular vote. But it is the Electoral College where the election is decided and, as the year 2000 reminded us, popular and electoral vote outcomes need not be the same. Thus, the traditional polls are of limited relevance. In this paper, we consider a shift in emphasis in polling to make the Electoral College central to the reported results. We offer evidence that doing so is not intractable and that, indeed, Electoral College polls that use the same sample sizes as national popular vote tallies have a comparable margin of statistical uncertainty. Thus, the opportunity is at hand to link pre-election polls to the system under which the President is actually elected.

The rules of the Electoral College are easy to state. In the College, the number of votes of any state is equal to its number of congressional representatives (two Senators, and one House member from each congressional district.) The District of Columbia gets three Electoral College votes. *All of*

a state’s Electoral College votes go to the candidate who wins the popular vote there (with slight exceptions in Maine and Nebraska). There are 538 electoral votes in total, so a candidate needs 270 such votes to win the presidency. The emphasis in this paper is on converting state-by-state polling results into a probability distribution for a candidate’s total number of electoral votes.

We start our work in the next section, where we model a candidate’s electoral vote distribution given estimates of the probability that (s)he is ahead for each of the 51 states (including D.C.). Then, we discuss how to obtain such state-specific probability estimates, based on “snapshot” polling results from each state and a “gentle” Bayesian prior (Section 3). We go on to illustrate our approach with several examples that use data from the 2000 campaign (Section 4). In Section 5, we consider how setting the goal as estimating electoral vote strength might affect the manner in which polling is conducted. How should a random sample of  $n$  voters, for example, be allocated across various states? In exploring this issue with data, we turn to the 1988 presidential election, which comes closer to typifying US presidential contests than other recent elections. In Section 6, we offer a summary and conclusions.

## 2 The Probability Distribution of Electoral College Votes

In this section we present a model for the probability distribution of the number of electoral college votes for a given candidate. We will first present the model, and then discuss the merits of the assumptions we have made.

We assume that all of the electoral college votes in a given state are allocated to that candidate who wins the largest number of votes in that state. There are 51 states in the election (corresponding to the 50 actual states plus Washington, DC). We focus on a particular candidate, and let  $p_i$  denote the probability that this candidate is genuinely ahead now in the popular vote in state  $i$ . There are  $v_i$  electoral college votes at stake in state  $i$ . We let the random variable  $V_i$  denote that actual number of electoral college votes won by the candidate in state  $i$ , and note that the probability distribution of  $V_i$  is given by

$$\Pr\{V_i = v\} = \begin{cases} p_i & v = v_i \\ 1 - p_i & v = 0 \\ 0 & \text{all other values of } v \end{cases} \quad i = 1, 2, \dots, 51. \quad (1)$$

We assume that the random variables  $V_i$  are mutually independent, as we discuss shortly.

Now define  $T_k$  as the total number of electoral college votes received by the candidate when considering states 1 through  $k$ . Clearly

$$T_k = \sum_{i=1}^k V_i \quad k = 1, 2, \dots, 51. \quad (2)$$

The expected value of  $T_k$  is given by

$$E(T_k) = \sum_{i=1}^k p_i v_i \quad k = 1, 2, \dots, 51 \quad (3)$$

while on account of the assumed independence of the random variables  $V_i$ , the variance of  $T_k$  is equal to

$$Var(T_k) = \sum_{i=1}^k p_i(1 - p_i)v_i^2 \quad k = 1, 2, \dots, 51. \quad (4)$$

Note that the total number of electoral college votes won by the candidate is equal to  $T_{51}$ . While the mean and variance of  $T_{51}$  follow from equations 3-4, we seek the probability distribution of  $T_{51}$ , for under the rules of the electoral college system,

$$\Pr\{\text{Candidate Wins Presidency}\} = \Pr\{T_{51} \geq 270\}. \quad (5)$$

To obtain the probability distribution of  $T_{51}$ , we first note that

$$T_{k+1} = V_{k+1} + T_k \quad \text{for } k = 1, 2, \dots, 50. \quad (6)$$

This permits us to argue recursively that for any state  $k$  and any number of electoral college votes  $t$ ,

$$\Pr\{T_{k+1} = t\} = (1 - p_{k+1}) \Pr\{T_k = t\} + p_{k+1} \Pr\{T_k = t - v_{k+1}\} \quad (7)$$

for  $k = 1, 2, \dots, 50$  and  $t = 0, 1, \dots, \sum_{i=1}^{k+1} v_i$ . Equation 7 is simply the convolution of the distributions for the independent random variables  $V_{k+1}$  and  $T_k$ . There are only two ways that the candidate could have received exactly  $t$  electoral college votes from the first  $k + 1$  states. Either (s)he lost in state  $k + 1$  but had already received exactly  $t$  votes total in states 1 through  $k$ , or (s)he won state  $k + 1$  and had already received exactly  $t - v_{k+1}$  votes in states 1 through  $k$ . Iterating through equation 7 enables us to efficiently obtain the entire probability distribution for  $T_{51}$ , from which we can employ equation 5 to calculate the probability of winning the presidency.

Some readers might wonder why we concern ourselves with deriving the “exact” probability distribution of electoral college votes via equation 7, for from equation 2 it is clear that we are considering the sum of several (51 to be exact) random variables, so perhaps something close to a normal distribution should be expected to hold in approximation. However, some reflection shows that there is no such guarantee. While the variables  $V_i$  are independent by assumption, they are by no means identically distributed. Suppose

that having considered all states except California, a normal approximation does work well for the distribution of  $T_{50}$ . However, suppose that the candidate in question also has a 50% chance of winning California's 54 electoral college votes. The final distribution of electoral college votes will then be an equally-weighted mixture of two normals spaced 54 votes apart, a result which is decidedly *not* well approximated by a single normal curve. As we will demonstrate later in this paper, the example described above is not simply a theoretical curiosity.

As noted, we assume that the random variables  $V_i$  are mutually independent, which is equivalent to assuming that the events that the candidate is leading in various states are mutually independent. What we are really assuming here is that the  $p_i$ 's are estimated based on polling results within the individual states, and largely reflect the imprecision caused by sampling error in such polls. There is no reason to believe that the sampling error in one state is in any way related to that in another. It is true that there are some historical correlations in election outcomes across states, but trying to exploit them for the distribution of the  $V_i$ 's seems far-fetched. Indeed, such correlations need not work against the independence assumption. For example, in the last 10 presidential elections, Massachusetts has voted for

the Democratic candidate 9 times while Minnesota has done so 8 times. If outcomes in the two states were statistically independent, one would expect Democratic victories in both of them in  $10 \times .9 \times .8 = 7.2$  times. The actual number of such double-wins was 7. Finally (and importantly), the model above yields results which are eminently reasonable when confronted with the actual results of the 2000 presidential election as we will discuss in Section 3.

### 3 Modeling the Probability of Winning a State

In this section, we present a model for the probability  $p_i$  that the candidate wins the popular vote (and hence all  $v_i$  electoral college votes) in state  $i$ . We assume for now that there are only two candidates contesting the election (an assumption we will defend shortly). Since the procedure to be described will apply to all states, we will drop state-specific subscripts in this section.

We presume that a random sample of the voting population is undertaken in each state to determine which candidate respondents prefer were the election held at the time of the poll. Denote the sample size of the poll by  $n$ , and let  $X$  denote the (random) number of respondents in the poll that favor

the candidate. As is commonly assumed, we take  $X$  to follow the binomial distribution with  $n$  trials and success probability  $\Pi$ , the fraction of voters in the state that favors the candidate. However, we treat  $\Pi$  itself as a random variable that, prior to polling, has a probability density  $f_{\Pi}(\pi)$ . After conducting a poll of size  $n$  and observing that the number of respondents that favor the candidate  $X = x$ , we obtain via Bayes' Rule the posterior density of  $\Pi$  as

$$f_{\Pi|X=x,n}(\pi|X = x, n) = \frac{f_{\Pi}(\pi) \Pr\{X = x|n, \Pi = \pi\}}{\int_{\pi'=0}^1 f_{\Pi}(\pi') \Pr\{X = x|n, \Pi = \pi'\} d\pi'} \text{ for } 0 < \pi < 1. \quad (8)$$

The probability  $p$  that the candidate wins the state is then modeled as

$$p = \Pr\{\Pi > 1/2|X = x, n\} = \int_{\pi=1/2}^1 f_{\Pi|X=x,n}(\pi|X = x, n) d\pi. \quad (9)$$

As is common in Bayesian estimation problems, we assume a beta prior density function for  $\Pi$ :

$$f_{\Pi}(\pi) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \pi^{\alpha-1} (1 - \pi)^{\beta-1} \text{ for } 0 < \pi < 1 \quad (10)$$

with mean and variance given by

$$E(\Pi) = \frac{\alpha}{\alpha + \beta} \quad (11)$$

and

$$Var(\Pi) = \frac{\alpha\beta}{(\alpha + \beta)^2 (\alpha + \beta + 1)} \quad (12)$$

as is well known. With this assumption, after observing  $x$  respondents who favor the candidate in a survey of  $n$  voters, the posterior distribution of  $\Pi$  is also a beta distribution, but with updated parameters  $\alpha + x$  and  $\beta + n - x$ .

In the applications that follow in the next section, we will work with “non-informative” prior distributions that set  $\alpha = \beta = 1/2$ . As detailed in Box and Tiao (1973), these values uniquely satisfy Jeffreys’ Rule (1961), which states that the prior distribution for a single parameter ( $\Pi$  in our application) is (approximately) noninformative if the prior is proportional to the square root of the Fisher information (Jeffreys, 1961). Noninformative priors “let the data do the talking,” as seems prudent when tracking voter sentiment over time. Note that other “weak” priors such as the uniform distribution would lead to nearly identical results in the applications to follow, so the reader should not worry that our choice for a prior has unduly influenced the analysis.

Updating the noninformative prior on the basis of (at least) moderately large sample sizes  $n$ , the posterior versions of equations 11 and 12 specialize to

$$E(\Pi|X = x, n) = \frac{x + 1/2}{n + 1} \approx \frac{x}{n} \tag{13}$$

and

$$Var(\Pi|X = x, n) = \frac{(x + 1/2)(n - x + 1/2)}{(n + 1)^2(n + 2)} \approx \frac{x}{n} \times \frac{n - x}{n} \times \frac{1}{n} \quad (14)$$

which are both familiar from standard sampling theory.

Several factors complicate the polls used in determining the  $p_i$ 's. There is the obvious point that, in several recent elections, a third party candidate was a potentially serious force (Anderson in 1980, Perot in 1992, Nader in 2000). In the actual election, such candidates rarely gain a single electoral vote, but the process by which their support “melts away” might affect the split of electoral votes between the two main candidates. (At any given time prior to the election, one could treat the supporters of third-party candidates as having abstained from the real two-candidate race, and could thereby exclude them from the estimation of the present  $p_i$ 's.) There are also undecided voters, and the chronic issue of how likely it is that a particular person canvassed will actually vote.

Such difficulties, of course, are already present in popular vote polls. It is not clear that focusing the polls on electoral vote totals makes the problems worse and, in some instances, such focus might lessen the problems. Suppose, for example, that a third-party candidate's support is concentrated in a few states and that, in every one of these states, his support is far smaller than the

spread between the two main candidates. Then electoral vote calculations should properly show the candidate's irrelevance to the election outcome. Statistics about his national level of popular support might be considerably less transparent.

Before moving to actual numbers, we should mention perhaps the worst-case scenario for our approach, in which one of the two candidates has 49.9% support in every state. Then his Electoral College strength is literally zero. But if we estimated his support from modest-sized state polls with margins of error, it is likely that his various  $p_i$ 's would average around 0.5. We would presumably project his mean number of electoral votes at around 269, while the 95% probability interval for his total (covering the 2.5%<sup>ile</sup> to the 97.5%<sup>ile</sup> of the electoral vote distribution) would come nowhere close to the true value of 0.

Such a monotonous pattern of razor-thin margins has no basis in US experience, so great worry about it is excessive. But even if the situation arose, it is not clear that our method really fails. The aim, after all, is to project who will be the next President. Given inevitable shifts over time in voter preferences, minuscule differences between candidates could often be reversed by Election Day. It might be more plausible to guess that the

trailing candidate will ultimately get 269 electoral votes than that he will get none at all.

To put it another way, the  $p_i$ 's might ideally reflect both the uncertainty in the candidate's standing at this time *and* the uncertain relationship between his support level now and his support in the election. In extremely close elections, the fact that our method does, however informally, respond to the second form of uncertainty is arguably more a strength than a weakness.

## 4 Examples From the 2000 Presidential Campaign

### 4.1 The American Research Group Poll of 30,600 Likely Voters

From September 5 through September 20 of 2000, the American Research Group (ARG) conducted a telephone survey of 600 likely voters in each state plus Washington, DC for a total sample size of 30,600. Those contacted were asked: "If the presidential election were being held today between George W. Bush, the Republican, Al Gore, the Democrat, Ralph Nader, from the

Green Party, and Pat Buchanan, from the Reform Party, for who would you vote - Bush, Gore, Nader, or Buchanan?” The order in which the candidates were named was rotated to remove potential sequencing biases. Using the standard  $1/\sqrt{n}$  formula to deduce a 4% margin of error, the ARG reported that Gore led in 15 states (i.e. held more than a 4 percentage point lead) with a total of 204 electoral votes, that Bush led in 17 states with a total of 132 electoral votes, and that the race was “too close to call” in the remaining 19 states with 202 electoral votes.

Applying our models to the state-by-state results of the ARG poll, we derived the probability distribution for the number of electoral college votes Al Gore would receive shown in Figure 1. According to this distribution, Gore would have expected 340 electoral college votes, with a standard deviation of 21. The 2.5%<sup>ile</sup>, median, and 97.5%<sup>ile</sup> of the distribution were, respectively, 296, 340, and 378. And, according to this distribution, the probability that Gore would have won the presidency had the election been held at the time of the survey equals 99.99%.

This last outcome emphasizes that phrases like “too close to call” and “statistical dead heat” can encourage us to discard highly useful information. If a candidate leads 52-48 in a poll with 600 voters, the chance that he is

ahead is not 50% but - even with our neutral prior - about 84%. Thus, the cumulative effect of several “too close to call” results might be an overall pattern that is not in the least too close to call.

## 4.2 State-by-State Polls: PollingReport.com

To explore the sorts of trends over time in presidential preferences our method might reveal, PollingReport.com granted us access to their database of state-specific voter surveys conducted over the course of the 2000 presidential campaign. This database contains polls conducted by many different polling organizations for newspapers, television stations, and political candidates. Most of these polls were telephone surveys of likely voters, though some interviewed registered voters. We aggregated the 468 different polls we reviewed into seven time periods: January through March, April through June, July, August, September, October 1-15, and October 16 on. Our intent was to create time periods long enough to cover most states, but short enough to enable us to observe trends over time. Also, given the large number of polls conducted as election day neared, we used the data collected from October 16 on to construct forecasts for direct comparison to the actual results of the election.

Unfortunately, polls were not conducted for all states in all time periods, and no polls conducted in Alaska, Kansas, South Dakota, or Washington, DC were present in the database. Our purpose here is to illustrate our methods, so we improvised as follows: for each state, we identified the earliest poll in the database, and then set the results for earlier missing time periods equal to the first-observed results. For example, the first poll conducted in Idaho that appears in the database was conducted in July, so we set the January-March and April-June Idaho results equal to what was observed in July. We filled in missing polls beyond the first available in similar fashion, only working forwards rather than backwards. So for example, polls conducted in Arkansas were reported in April-June, July, September, and October 16 on. We set the January-March results equal to those observed in April-June, the August results equal to those observed in July, and the October 1-15 results equal to those observed in September. For Alaska, Kansas, South Dakota, and Washington, DC, we simply substituted the results of the September American Research Group in all time periods. We discarded undecided voters as well as those with a preference for a candidate other than George Bush or Al Gore, and employed noninformative beta priors at the start of each time period. We describe the results below.

#### 4.2.1 The Electoral College Distribution as of January-March 2000

As a vivid illustration of why we rely on equation 7 to compute the probability distribution of the number of electoral college votes, Figure 2 shows the distribution of Al Gore's electoral college votes as estimated from the January-March entries in the PollingReport.com database (after adjusting for missing entries as explained above). The distribution is clearly a mixture of two subdistributions with a separation of 54 votes. As stated in the figure, California is the key. A January 15 poll and a February 2 poll, both conducted by the Public Policy Institute of California, reported 466 (466) and 456 (466) respondents favoring Bush (Gore) in the respective poll. Taken together, the posterior probability that Gore would receive more than 50% of the vote in California given these data and a noninformative prior equals 0.59, which explains the otherwise odd shape of the electoral college distribution. Note that according to the distribution in Figure 2, Gore would have had no chance of winning the election as with probability 1, the number of electoral college votes he would have received would have fallen below the 270 required for victory.

#### 4.2.2 Trends in the Electoral College Distribution and the Probability of Winning the Presidency

Figure 3 reports the probability distributions of Al Gore's electoral college votes for all seven time periods. Together these distributions suggest a growing wave of support for Gore over the course of the campaign. Figure 4 reports the median and 95% probability intervals of these probability distributions. The figure shows that the median number of electoral college votes for Gore jumped from about 180 in the first half of 2000 to about 285 as the election neared.<sup>1</sup> Figure 5 portrays starkly the changes in Gore's probability of winning the election over time as implied by the PollingReport.com data. Gore's chance of winning went from literally nothing in the first half of 2000 to an average of about 85% in the months preceding the election. Figure 6 compares the likelihood of Gore winning over time to the raw overall fraction favoring Gore as evidenced in the PollingReport.com database. It is revealing to note how very small changes in the latter translate to large differences

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<sup>1</sup>The estimate of Gore's strength based on the September PollingReport.com data is lower than that in the concurrent AMR poll (with a median of 285 electoral votes versus 340). The difference reflects methodological divergences between the two sampling procedures that, while important, are not germane to the main point of this paper.

in the former, highlighting the proposition that it is precisely in very tight races where the idiosyncracies of the electoral college system for choosing the president matter the most (and where our proposed approach might yield the most valuable information).

#### 4.2.3 The Actual Election: An “Out of Sample” Experience

The polls from October 16 on provide a nearly complete data set (only Connecticut, North Dakota, Utah and Wyoming are missing in addition to the four states identified earlier) sufficiently close to the actual election to make a comparison between the surveys and the actual election meaningful. The comparison is even more meaningful if we exclude the state of Florida and the associated ballot confusion in Palm Beach County. Excluding Florida, our model suggests that Gore could have expected 262.5 electoral college votes with a standard deviation of 12. Gore won the rights to 267 electoral votes (though he actually received only 266, as one elector from Washington, DC refused to vote as a protest against DC’s lack of representation in the United States Congress), well within the chance bounds of our model. Comparing our individual state forecasts with actual state results, we find that the projected winner actually won in all but four states (Delaware, Missouri,

Oregon, and Florida). In these states, the trailing candidate was assigned a chance of winning between 14% and 37%. If the trailing candidate is estimated to have probability  $q_i$  of winning state  $i$ , then we would expect to be “surprised”  $\sum_{i=1}^{51} q_i$  times; for these data,  $\sum_{i=1}^{51} q_i = 3.7$ . Thus, in some sense, the reversals we saw are more consistent with our model than an absence of reversals would have been.

## 5 Allocating a Fixed Sample Size

Until now, we have applied our model in opportunistic fashion using whatever polls we were able to locate for analysis. Suppose instead that one wished to adopt our procedures prospectively for use in future presidential elections. An important design question to answer is, how should a sample of fixed total size be allocated across the states? Thinking of the entire electoral college probability distribution, we propose an approach in this section that focuses on minimizing the variability of that distribution. More precisely, we seek to minimize the *prior* expectation of the *posterior* variance of the electoral college distribution.

Given that the distribution of a candidate’s electoral votes need not be

normal, minimizing the variance is not equivalent to minimizing variability under other criteria (e.g. achieving the narrowest 95% probability interval for the candidate's standing). But focusing on the variance is a reasonable approach that preserves tractability.

We continue to focus only on the case of two candidates, and let  $n_i$  denote the number of persons sampled in state  $i$  who have a preference for either the Republican or the Democrat. Suppose that having sampled  $n_i$  persons with such preferences in state  $i$ , we discover that  $x_i$  favor the candidate in question. From equation 9 recall that given this result, the probability that the candidate wins state  $i$  is, in an obvious notation, modeled as

$$p_i(x_i, n_i) = \Pr\{\Pi_i > 1/2 | X_i = x_i, n_i\} = \int_{\pi=1/2}^1 f_{\Pi_i | X_i = x_i, n_i}(\pi | X_i = x_i, n_i) d\pi. \quad (15)$$

The posterior variance of the number of electoral college votes in state  $i$  given that  $x_i$  respondents favor the candidate is then given by

$$\sigma_i^2(x_i, n_i) = p_i(x_i, n_i) \times (1 - p_i(x_i, n_i)) \times v_i^2. \quad (16)$$

Now, recall that the distribution of the number surveyed in state  $i$  that favor the candidate,  $X_i$ , is distributed binomially with parameters  $n_i$  and  $\Pi_i$

where  $\Pi_i$  itself has a prior density  $f_{\Pi_i}(\pi)$ . The marginal prior distribution of  $X_i$  given the sample size  $n_i$  is then the mixture of binomials given by

$$\Pr\{X_i = x_i | n_i\} = \int_0^1 \Pr\{X_i = x_i | n_i, \Pi_i = \pi\} f_{\Pi_i}(\pi) d\pi. \quad (17)$$

The *prior* expectation of the *posterior* variance of the number of electoral college votes for the candidate in state  $i$  is thus given by

$$\bar{\sigma}_i^2(n_i) = \sum_{x_i=0}^{n_i} \sigma_i^2(x_i, n_i) \times \Pr\{X_i = x_i | n_i\}. \quad (18)$$

Our proposal for allocating a sample of  $n$  two-party respondents is to solve the following knapsack problem:

$$\min_{n_1, n_2, \dots, n_{51}} \sum_{i=1}^{51} \bar{\sigma}_i^2(n_i) \quad (19)$$

subject to the constraints

$$\sum_{i=1}^{51} n_i = n \quad (20)$$

and

$$n_i \geq 0 \text{ and integer for } i = 1, 2, \dots, 51. \quad (21)$$

Solving this sample allocation problem is aided greatly by the observation that the functions  $\bar{\sigma}_i^2(n_i)$  are decreasing and convex. This means that a

marginal allocation (or *greedy*) algorithm will provide the optimal solution. In such a scheme, each sample is allocated to that state with the largest *marginal* reduction in uncertainty. More formally, define

$$\Delta_i(n_i) = \bar{\sigma}_i^2(n_i) - \bar{\sigma}_i^2(n_i + 1) \quad (22)$$

and initially set  $n_i = 0$  for  $i = 1, 2, \dots, 51$ . Let  $m$  be a counter that will run from 1 through  $n$ . Then the algorithm runs as follows:

#### Marginal Allocation Algorithm

For :  $m = 1$  to  $n$

Define :  $i^* = \arg \max_{1 \leq i \leq 51} \Delta_i(n_i)$

Set :  $n_{i^*} \leftarrow n_{i^*} + 1$

Next :  $m$

Ties can be broken arbitrarily in defining  $i^*$  in the algorithm above. We will next present some examples illustrating the use of this algorithm, and then show how to account for the obvious point that in actual surveys, respondents will express preferences for third party candidates or fail to express a preference altogether.

## 5.1 The American Research Group Poll Revisited

Recall the 30,600 person state-by-state American Research Group poll. Of the 30,600 persons sampled, 26,076 expressed a preference for George Bush or Al Gore. Assuming noninformative priors, had these 26,076 observations been allocated in accord with the marginal allocation algorithm, the *prior* expectation of the *posterior* variance in the electoral college distribution would equal 80.66, which implies a pseudo-standard deviation of 8.98, or about 1.7% of the electoral-vote total. Suppose that the American Research Group faced a factor-of-ten budget slash and wished to optimally allocate 2,000 Bush/Gore samples across the states. Again assuming noninformative priors, the marginal allocation algorithm achieves a variance of 197.5, with an associated standard deviation of 14.05, 2.6% of the number of electoral votes.

## 5.2 Optimal Sample Size as a Function of the Number of Electoral College Votes: Noninformative Priors

Continuing with the use of noninformative priors, Figure 7 reports how the optimal sample allocations determined by the marginal allocation algorithm

vary with the number of electoral college votes at stake for total sample sizes of 500, 1,000, 1,500, and 2,000. The optimal sample sizes increase in convex fashion with the number of electoral college votes. This is not surprising when one realizes that the prior expectation of the posterior variance of the number of electoral votes in state  $i$ ,  $\bar{\sigma}_i^2(n_i)$ , is proportional to  $v_i^2$ . In trying to estimate the distribution of electoral college votes, getting California right is clearly more important than North or South Dakota!

### 5.3 Optimal Sample Size with “Last Minute” Informative Priors

To illustrate how one can proceed with a prior that incorporates the latest polling data, imagine the following scenario: a political consultant, aware of the survey results from a family of polls taken prior to the election, decides to use the results of these polls to form “last minute” informative priors for allocating a sample with a target total of 500 Bush/Gore respondents. We assume that the consultant has access to prior polls with sample size  $m_i$  in state  $i$ . Having observed a fraction  $g_i$  for Gore in the prior sample, she updates her noninformative prior for  $\Pi_i$  as described in Section 3. As a numerical example, we consider the proportions favoring Gore reported in

the last wave of PollingReport.com data, but we reduce the prior sample size  $m_i$  to 10% of the total number of Bush/Gore respondents in the data to better reflect the information an individual consultant might have at her disposal (since many of the polls in the data were private at the time).

The results are shown in Table 1. Not surprisingly, in most states the priors are sufficiently strong to obviate the need for further sampling. Sampling would only progress in eight states under this scenario. Of the 500 samples sought, 279 would have been allocated to Florida, a state with both a tight race and a large number (25) of electoral college votes at stake. The situation in California was more certain, but with 54 electoral college votes, it would still be prudent to collect an additional 77 samples there. Table 1 also shows that it might not always be worth it to take the results of the marginal allocation algorithm literally - is it really that important to obtain two additional samples from Arizona, three from New Mexico, and 6 from Colorado? Including these samples leads to an expected posterior variance of 793.4, while excluding them raises this to 794.4, a trivial change.

## 5.4 An Experiment with the 1988 Election

To assess the power of our methods for projecting Electoral College results, we turn to the 1988 election for an experiment. That year, George Bush Sr. defeated Michael Dukakis, gaining 426 of the 538 electoral votes and 54% of the popular vote. The 1988 election was the most “normal” of recent contests: In 1984 and 1996, there were landslides, while in 1992 Ross Perot launched the strongest third-party candidacy in recent memory. The premise of the experiment is that a pollster can canvass  $n$  voters across the nation on the eve of the election, and that polling in individual states will reflect without bias how the state will vote on Election Day. Thus, for example, Dukakis got 43% of the vote in New Jersey; we therefore assume that any person polled in that state would have a .43 chance of supporting Dukakis and a .57 chance of supporting Bush.

We allowed the total number of voters polled to vary, from an average of 10 per state (510 voters in all) to 150 per state (7650 in total). We also allowed the allocation of samples across the states to vary according to four different schemes:

1. Homogeneous - The same sample size in all 51 states
2. Simple Marginal Allocation - Samples are allocated across states ac-

ording to their electoral vote totals, so as to minimize posterior variance (as described in Section 5)

3. Homogeneous/Marginal Hybrid - First, half the sampling is divided equally among the 51 states. Then, the initial results are used to achieve revised distributions of state vote splits. These distributions are used in the marginal allocation algorithm to set the numbers sampled in each state among the remaining  $n/2$  people polled.

4. Marginal/ Marginal Hybrid - Here the first  $n/2$  samples are divided among states according to the allocation algorithm. Then, the results generate a revised distribution of state vote-splits, which is then used in a second run of the marginal allocation algorithm for the remaining  $n/2$  samples.

In all we considered six values of  $n$  and four sample-allocation rules, yielding a total of 24 results. The basic procedure in each instance was:

(i) Take a sample of size  $m$  in each state, and assume that the observed number for Dukakis would be binomially distributed with  $m$  trials and success probability  $q$ , where  $q =$  Dukakis' actual share of the vote on Election Day in 1988. (As noted,  $m$  might partially depend on outcomes in the first half of the sampling.)

(ii) Use the observed sampling result and the Bayesian prior as in Section

3 to estimate the probability that Dukakis would carry each state (i.e., its  $p_i$ ).

(iii) Go back to the original recursion of equation 7 in Section 2 to find the probability distribution for Dukakis' total number of electoral votes.

Table 2 summarizes the results of the experiment. In each instance, we present the 2.5%<sup>ile</sup>, the median, and the 97.5%<sup>ile</sup> of the estimated number of Dukakis electoral votes (recall that the 95% probability interval for the total is the range from the 2.5%<sup>ile</sup> to the 97.5%<sup>ile</sup>.) Dukakis actually won 112 electoral votes.

The results are generally encouraging, though not without some disappointments. In all 24 scenarios, Dukakis was accurately assigned a small chance of winning the presidency. The probability was about 5% when 2040 people were polled (mean of 40 per state), and fell to about 1 in 1000 when an average of 150 people were polled per state. But there was a systematic tendency to overestimate Dukakis' electoral-vote total. Although his actual showing fell within the 95% probability interval once  $n$  reached 2040, he was below the median even for  $n = 7650$ .

We suggested the reason for this latter tendency earlier, where we noted that our method might overestimate the chance a candidate will win a state

when he is only modestly behind there. The Bayesian prior starts by assigning  $p_i = .5$ , and only gradually moves from that assessment as polling data come in. If, for example, only 20 voters are selected in a state in which the true Dukakis vote-share is .44, then even an “accurate” vote split of 9 for Dukakis and 11 for Bush would only push  $p_i$  down to 0.33. The problem would ultimately disappear once sample sizes got huge; as the calculation suggests, however, huge might mean considerably larger than typical national polls.

Of course, large state-by-state polls routinely take place for various reasons, as we saw in 2000. Thus, if the Electoral College poll could sensibly “piggy back” on individual-state surveys already undertaken, then achieving very high accuracy need not entail inordinate extra expense.

Perhaps counterintuitively, the homogenous/marginal allocation method fared better in the experiment than the marginal/marginal method. The danger to the latter approach might be its predisposition to favor the larger states in the first half of canvassing, even though uncertainty about outcomes might be greater in smaller states. Thus, samples wasted on “belaboring the obvious” in large states might preclude enough sampling in close small states to provide reliable information there.

## 6 Summary

National voter surveys estimate the likely popular vote, but such polls do not directly estimate the probability of winning the presidency. We have presented a model for determining the probability distribution of the number of electoral college votes that a candidate will win. From this distribution, one can compute directly the probability of winning the presidency. We have shown how to derive the necessary parameters for this model via Bayesian analysis of state-by-state voter surveys, and we have illustrated our methods with polls conducted during the 2000 presidential campaign. We have also examined the problem of how to efficiently allocate a sample across the states, developed a very simple marginal allocation algorithm for solving this problem, and illustrated via recourse to the 2000 and 1988 contests. It remains to apply these methods prospectively in a future presidential election. Stay tuned.

## References

- [1] Box, G.E.P. and Tiao, G.C. (1973). *Bayesian Inference in Statistical Analysis*. Reading, Massachusetts: Addison-Wesley.

- [2] Jeffreys, H. (1961). *Theory of Probability*, third edition. Oxford: Clarendon Press.

Table 1  
Optimal Sample Sizes  
(Informed Priors,  $n = 500$ )

State	Optimal Sample Size
Arizona	2
California	77
Colorado	6
Florida	279
Georgia	25
New Mexico	3
North Carolina	85
Pennsylvania	23

**Table 2**

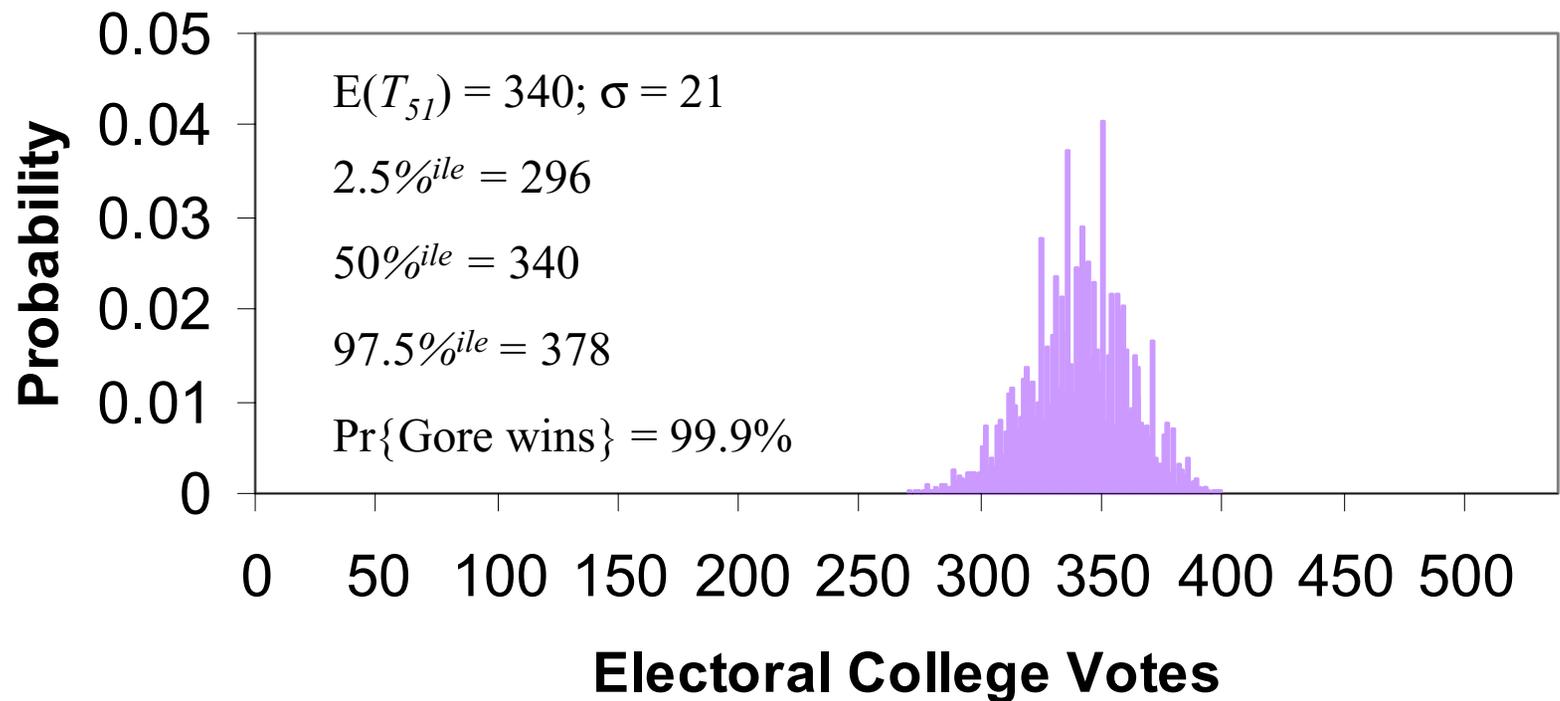
**Results from the 1988  
Dukakis Electoral College Distribution Experiment**

**(2.5%<sup>ile</sup>, Median, 97.5%<sup>ile</sup>, and Pr{Dukakis Wins})**

<b>Sample Size</b>	<b>Homogeneous</b>	<b>Marginal Allocation</b>	<b>Homogeneous/ Marginal Hybrid</b>	<b>Marginal/ Marginal Hybrid</b>
	<u>2.5%/50%/97.5%/Pr{Win}</u>	<u>2.5%/50%/97.5%/Pr{Win}</u>	<u>2.5%/50%/97.5%/Pr{Win}</u>	<u>2.5%/50%/97.5%/Pr{Win}</u>
510	136 / 229 / 325 / 0.213	135 / 225 / 321 / 0.1897	130 / 221 / 317 / 0.165	136 / 226 / 322 / 0.1934
1020	124 / 214 / 310 / 0.134	123 / 210 / 304 / 0.1121	117 / 203 / 297 / 0.0868	120 / 205 / 299 / 0.0917
2040	109 / 196 / 289 / 0.0635	109 / 191 / 282 / 0.0463	102 / 183 / 274 / 0.0309	107 / 186 / 276 / 0.0342
4080	93 / 176 / 289 / 0.0196	95 / 170 / 255 / 0.0107	88 / 162 / 247 / 0.006	95 / 166 / 249 / 0.0069
5100	89 / 169 / 257 / 0.012	91 / 163 / 246 / 0.0056	84 / 156 / 238 / 0.003	92 / 159 / 239 / 0.0034
7650	81 / 158 / 243 / 0.0041	85 / 152 / 230 / 0.0013	79 / 145 / 222 / 0.0006	87 / 148 / 222 / 0.0007

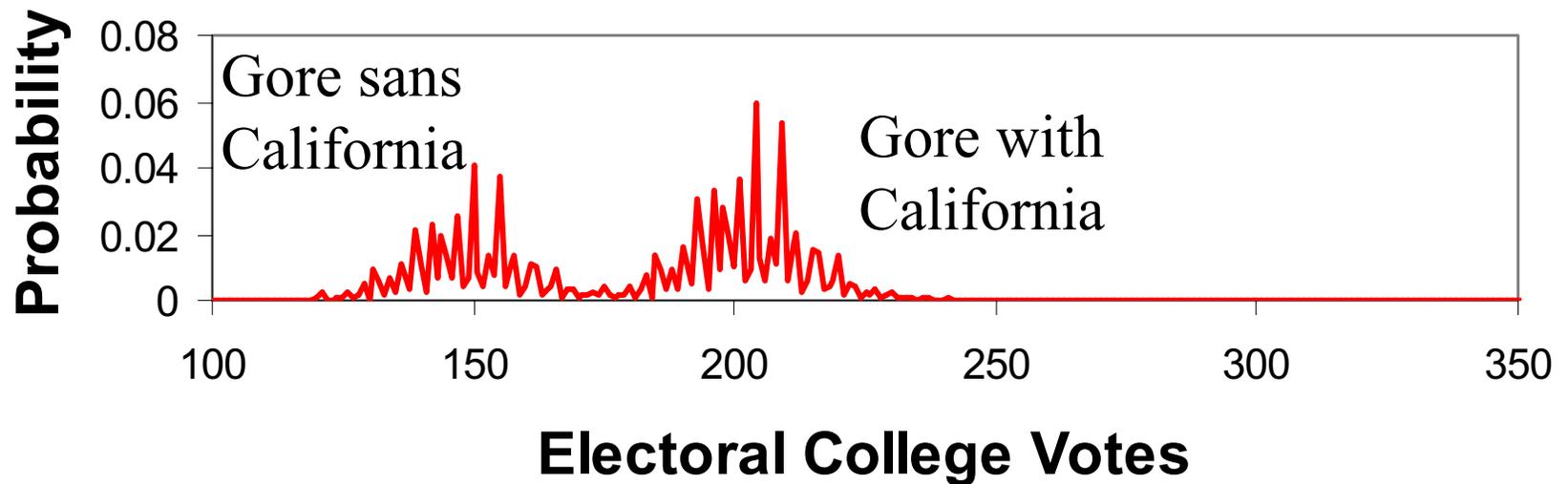
# Figure 1

Probability Distribution of Gore's Electoral College Votes (based on ARG Survey of 9/5-9/20, 2000)



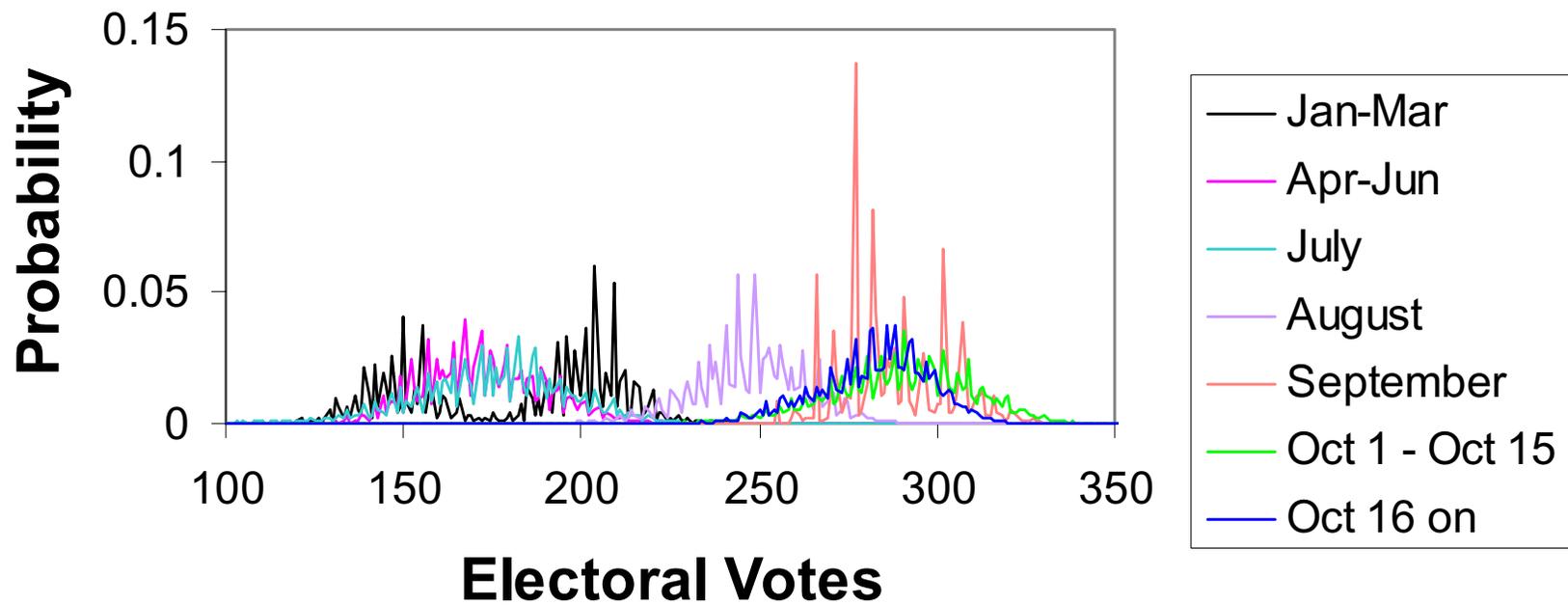
## Figure 2

### Probability Distribution of Gore's Electoral College Votes: Jan - Mar, 2000 (based on PollingReport.com)

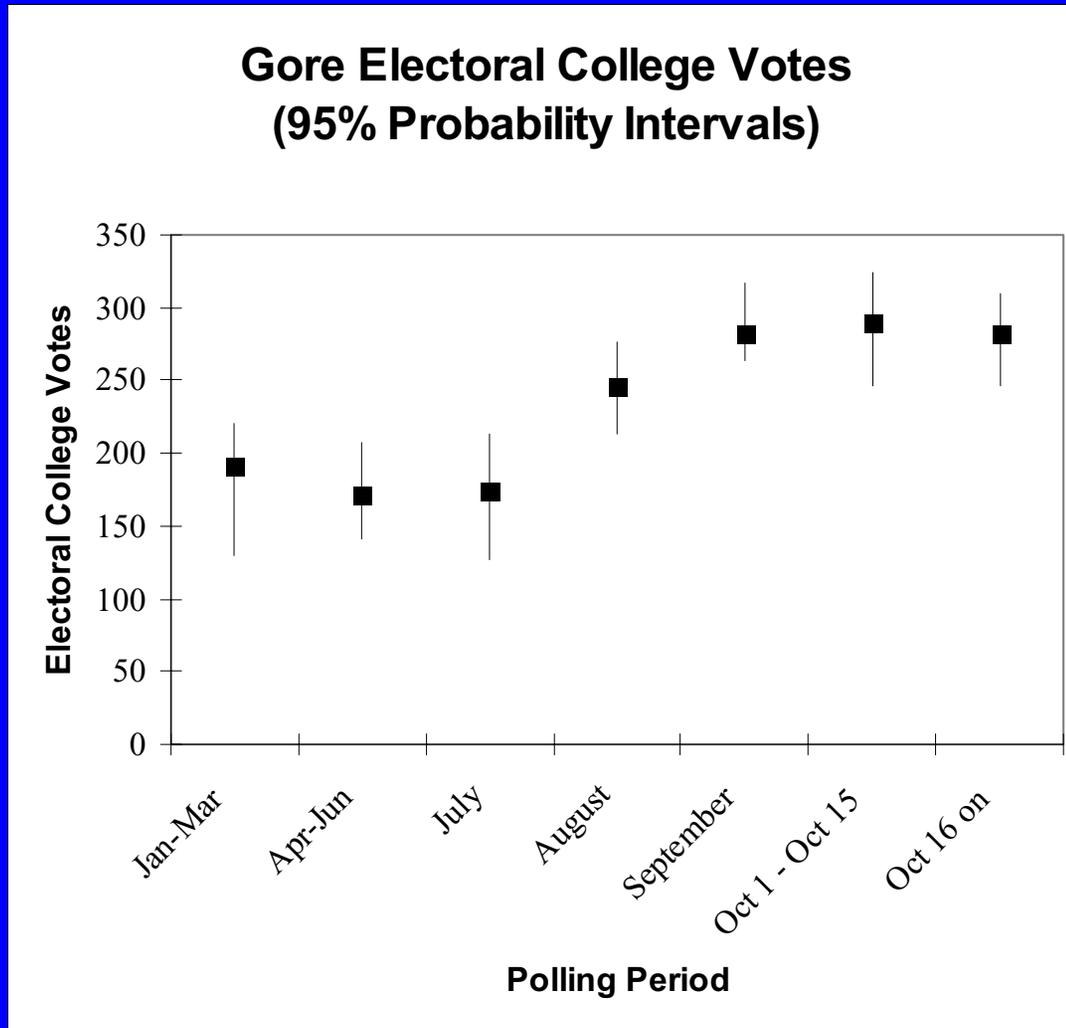


# Figure 3

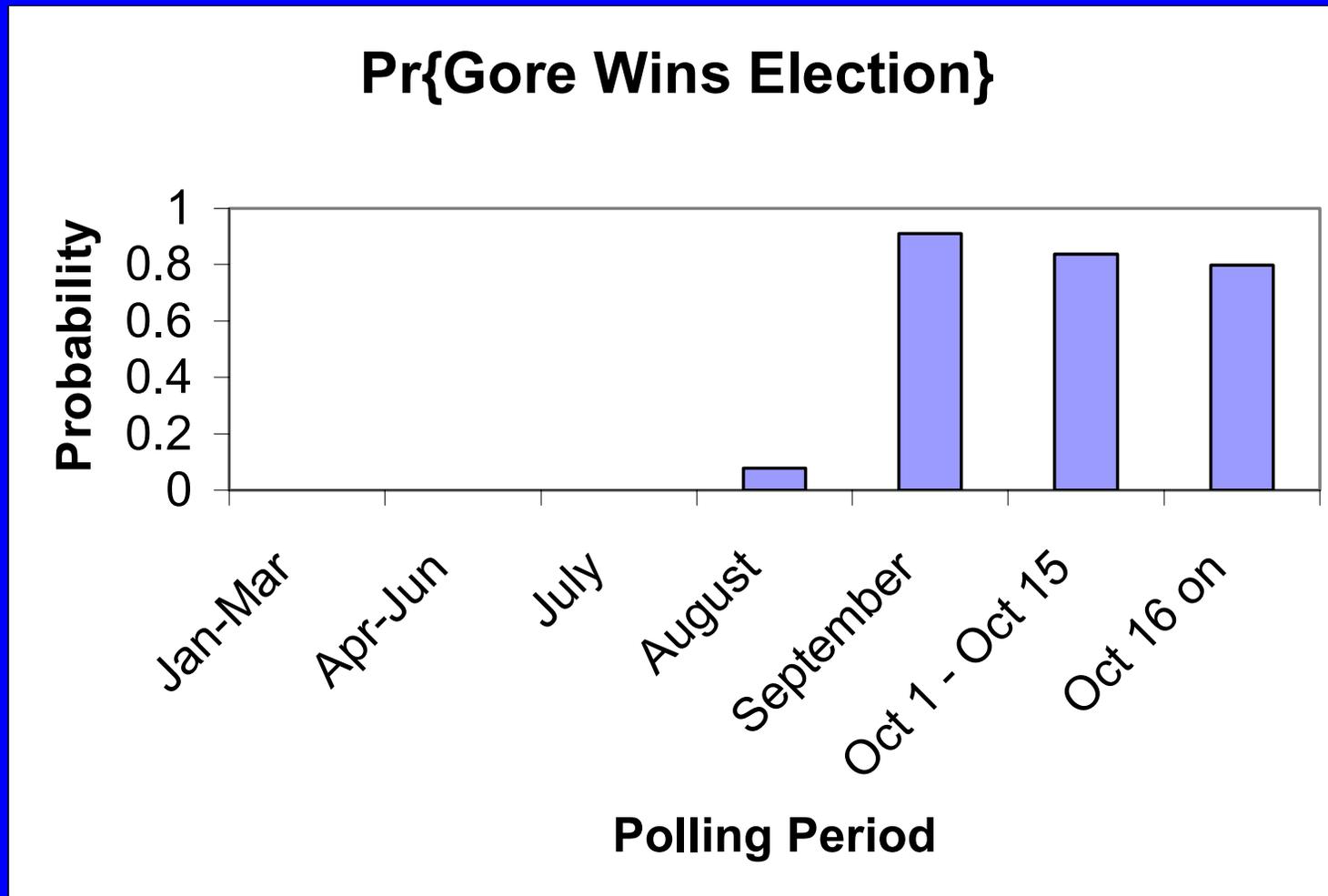
## Electoral College Distributions: Electoral Votes for Gore



# Figure 4

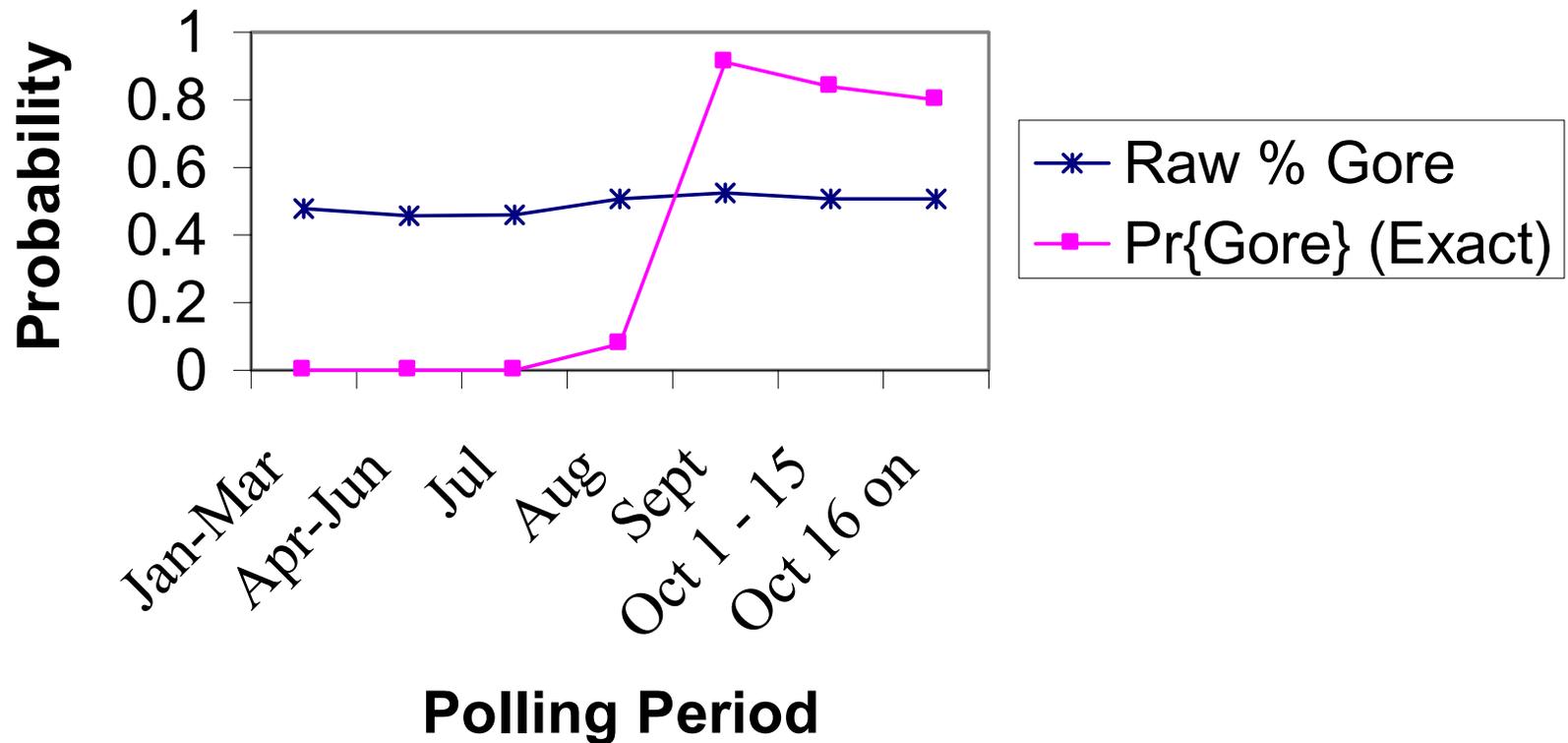


# Figure 5



# Figure 6

## Gore's Popular Vote vs Pr{Gore Wins}



# Figure 7

