One in a Million: A Field Experiment on Belief Formation and Pivotal Voting*

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Abstract

Instrumental voting models predict that turnout depends on the chance of casting a pivotal vote, which is typically extremely low in large elections. Evidence from psychology and behavioral economics suggests that misperceptions of extremely unlikely events are common and subject to systematic biases, sometimes called the non-belief in the law of large numbers. We provide a model of voting when voters suffer from these biases and show that they inflate the perceived pivot probabilities, and hence turnout. Moreover, voters do not fully account for new information of pivot probabilities in this model. We then test the model in a large-scale field experiment during the 2010 U.S. gubernatorial elections where we elicited voter beliefs about a very close election before and after showing different polls. We find that voters massively inflate pivot probabilities and this inflation is most pronounced among subjects measured to have the highest non-belief in the law of large numbers. Furthermore, subjects respond to but fail to fully incorporate new information presented in the experiment. However, the decision to vote is not affected by beliefs about pivotality. Even in a controlled setting and in response to an experimental manipulation that significantly changed the perceived probability of being pivotal, voting behavior is unaffected.

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1 Introduction

Why do people vote? The process by which individuals decide whether and for whom to vote is one of the most enduring and important questions in political economy. Despite a plethora of hypotheses and a wealth of data, many puzzles persist, particularly with regard to turnout. For instance, even across similar wealthy countries, differences in voting behavior are stark. The U.S. exhibits low voter turnout as well as large disparities in turnout by socioeconomic status. The canonical theory of voting, dating back to Downs (1957), postulates that voters are mainly concerned with electoral outcomes; that is, voting is an instrumental process to achieve the rational end of obtaining one's preferred alternative from among those on offer. Thus, in deciding whether and for whom to vote, a voter weighs the net benefit from obtaining her most preferred outcome multiplied by the chance that her vote is decisive, or pivotal in the parlance of political economy. This expected benefit is weighed against the cost of voting and, only if the benefit outweighs the cost will a voter turn out at the poll.

This theory is often criticized for its implications on turnout. The inexorable arithmetic of pivotal probabilities imply that the chance of casting a decisive vote falls precipitously as turnout increases, and so, unless the benefits from obtaining one's preferred candidate are exceptionally high or costs exceptionally low, the voting calculus favors staying at home, leading to unreasonably low turnout percentages. Indeed, so long as the benefits are finite and the costs non-negative, the theory predicts that the turnout percentage will approach zero in a large election. This is obviously grossly at odds with the data. The conundrum, often called "the paradox of voting," has led researchers to look for ways to amend the voting calculus; thereby obtaining a more satisfactory solution. Downs speculated that the pang of conscience, the duty as citizen to vote, could reconcile the paradox to the data. Under this theory, first formalized by Riker and Ordeshook (1968), citizens experience a loss from shame or guilt in staying away from the polls. These voters have, in effect, negative voting costs and turn up at the polls even if the expected benefit from voting is approximately zero. Subsequent research, including Fiorina (1976), Feddersen and Sandroni (2006), Benabou and Tirole (2003), Funk (2010), and Morgan and Vardy (2013) explore the implications of this insight on turnout and voting outcomes.[1]

In this paper, we examine, both theoretically and empirically, another aspect of the calculus of voting: the misperception of pivotal probabilities. There is by now a large literature in psychology and behavioral economics showing that beliefs of individuals about the likelihood of certain events often diverge from the true mathematical properties in systematic ways. This divergence is particularly acute in calculating extremely unlikely events, such as the probability of casting a decisive vote in a large election. We explore what Kahneman and Tversky (1972) dubbed the *non-belief in the law of large numbers* (NBLLN). This phenomenon consists of two types of cognitive errors: Individuals tend to misperceive the nature of the underlying distribution of probabilities, ascribing fatter tail probabilities than are warranted. In addition, individuals tend to underweight the precision of a large sample; in effect, inflating the sample standard deviation as the number of draws becomes large.

[1]For a theory of voting based on the desire to telling one's friends that one voted, see DellaVigna et al. (2013).

Our contribution is to show that the non-belief in the law of large numbers leads to a systematic misperception and inflation of pivot probabilities, particularly in large elections. As a consequence, individuals view the expected benefit from voting in a large election as non-negligible and turn out to vote even in the absence of motives such as civic duty. This is not to say that duty has no role to play, but rather to point out a complementary effect from the misperception of pivotal probabilities. Both effects work in the direction of increasing turnout relative to the canonical model. Building on Benjamin et al. (2012b) formalizing the non-belief in the law of large numbers, we apply their framework to the study of pivotal probabilities. The two main implications of the theory are: (1) Individuals subject to NBLLN inflate pivotal probabilities such that they remain bounded away from zero, even in the limit as the electorate grows large; and (2) individuals subject to NBLLN underreact to new information, even if it arises from a large and representative poll, instead clinging to prior beliefs.

We then test these implications in a large-scale field experiment consisting of 16,000 voters during the 2010 gubernatorial elections. Using computer surveys with potential voters in 13 U.S. states, we asked voters their beliefs about the chance that the state gubernatorial election would be very close. We then exposed these voters to different informational treatments to assess the impact of new information on their beliefs and behavior. Exploiting the variation in poll results prior to the election, we divided subjects into three groups. The control group received no polling information. We informed the "not close" group of the results of a poll indicating the greatest gap between the two candidates. We informed the "close" group of the results of a poll indicating the narrowest margin between the candidates. Following this, we then observed the impact of this information by subsequently asking them the chance the election would be very close. Finally, we used administrative data to determine whether our survey respondents did, in fact, turn up to vote. To gauge subjects susceptibility for the non-belief in the law of large numbers, we also conducted a "lab experiment in the field" using a design introduced by Benjamin et al. (2012a), which provided a measure of NBLLN.

We obtained two main findings from these experiments. First, both belief formation and updating are strongly consistent with a non-belief in the law of large numbers. Subjects dramatically overestimate the probability of a very close election. The median probabilities that the gubernatorial election would be decided by less than 100 or less than 1,000 votes were 10% and 20%, respectively. Even among the 1400 voters with Masters and PhD degrees, the median perceived probabilities of less than 100 and less than 1,000 votes were 5% and 10%, respectively. Moreover, subjects who scored high in our NBLLN measure also exhibited a stronger tendency to overestimate the chance of being pivotal and to update less when presented with poll results. In addition to our directional findings, we estimate a structural model of NBLLN to see how well the model can explain the data and to summarize the degree of NBLLN in a single parameter that can be compared across domains.

Second, although beliefs imply a high and changeable expected benefit from voting, this does not translate into behavior as predicted by the instrumental models of voting, even with the amendment of the misperception of pivotal probabilities. Indeed, voter turnout was, statistically, independent of differences in beliefs about the chance of casting a decisive vote. This suggests that non-instrumental considerations, such as expressive voting, loom larger in the minds of voters determining whether and for whom to vote. We are pains to stress that we have no direct evidence of these alternative considerations; nonetheless, the results are simply inconsistent with an electoral calculus whereby voter compute the expected benefit of voting (perhaps incorrectly) and then adjust turnout and voting behavior accordingly.

To summarize, the two contributions of the paper are (1) to postulate and then demonstrate that non-belief in the law of large numbers plays a significant role in pivotality calculations of voters, and (2) to show that differences in beliefs about pivotality seem to play no role in actual turnout. To the best of our knowledge, we are the first to study the relationship between beliefs about pivotality and voting in the field, as well as the first to provide field evidence on the non-belief in the law of large numbers.

Before proceeding, it is helpful to place the work in context. It is well-known that turnout tends to rise in close elections, which is broadly consistent with an instrumental theory of voting and turnout.[2] But there are many confounds in simply comparing turnout across elections. Close elections tend to attract more advertising and news coverage leading up to the vote compared with landslides. Close elections, like sporting events, are more interesting to monitor and discuss than walkovers. Coate et al. (2008) overcome these confounds by examining turnout across towns in Texas voting on whether to legalize the sale of liquor. Since the towns varied in size, so did the chance of being pivotal. Coate et al. (2008) found higher turnout in smaller towns than in larger. Even this study is not immune to confounding factors, most notably variations in the sense of "duty" across towns.. Turnout is more readily monitored in small towns than in large cities, and this may alter the costs of remaining at home. Indeed, in a study of the introduction of voting by mail in Swiss cantons, Funk (2010) noted that turnout fell by a greater amount in smaller communities than in large, presumably because the social enforcement of voting was greater.

Rather than relying on natural experiments, we experimentally manipulate individual beliefs about the chance of casting a decisive vote. This has the advantage of eliminating confounds, but the disadvantage that the manipulation lacks power. For instance, if subjects were voracious consumers of polling data, then our informational treatment should have no effect, as no new information was, in fact, presented. The belief response of subjects plus introspection about how interesting gubernatorial polling data is to an average person, suggests this was not the case.

Many laboratory experiments of voting have manipulated the chance of being pivotal and found effects on voting decisions (e.g. Tyran, 2004). Mainly, these papers are concerned with expressive voting, which should manifest itself more when pivot probabilities are small rather than large. There are several important differences between laboratory studies and our setting. First, the size of the elections is considerably smaller and, indeed, the chance of being pivotal in any of these studies are orders of magnitude larger than in statewide gubernatorial races. Second, and perhaps more importantly, pivotal probabilities in laboratory experiments represent objective probabilities rather than subjective. Indeed, subjects are often informed about their precise chance of being pivotal.

[2] Foster (1984) and Matsusaka and Palda (1993) contain extensive surveys of the literature on turnout.

Finally, none of these studies concerns itself with the non-belief in the law of large numbers.[3]

We are aware of no other field experiments that randomly assign polls to voters so as to examine the impact on turnover. Since our field experiment was conducted in 2010, Agranov et al. (2012) conducted a lab experiment where voters were assigned different polling information. In addition, we are aware of very few studies that seek to measure or influence voter beliefs about electoral closeness. Delavande and Manski (2010) measure voter beliefs about the probability of a very close election in the RAND Life Panel, but do not experimentally manipulate them.[4]

Our paper also also links with the small literature on non-Bayesian beliefs and updating. In doing so it builds on the model of Benjamin et al. (2012b). While there is an extensive literature estimating models of beliefs and learning in games (examples of this literature include Camerer et al. (2002) and Crawford et al. (2012)), the literature on structurally estimating models of beliefs and updating using field data is much smaller.[5] Third, because the paper also experimentally elicits a measure of NBLLN it touches on a literature that links experimental measures of parameters to real-world beliefs and behavior, discussed in detail in Camerer (2011).

The rest of the paper is as follows. In Section 2 we develop our theory of NBLLN and voting. Section 4 describes the design of our field experiment, as well as the lab experiment designed to measure NBLLN. Section 5 describes the reduced-form results of the field experiment. Section 6structurally estimate the degree of NBLLN implied by voter beliefs. Section 7 concludes.

2 Model

There are two candidates, A and B, who differ only in their ideology. Voters either prefer A or B and the strength of preference for all voters preferring A is $v_A \in (0,1)$ while $v_B \in (0,1)$ is the strength of preference for those preferring B. The strength of preference can be understood to be the difference in a voter's instrumental payoffs from comparing outcomes A and B. Let θ denote the probability that a voter prefers A. The realized state is unknown to voters; thus, the model contains aggregate uncertainty in the sense of Myatt (2011), Mandler (2008), and Krishna and Morgan (2013).

The number of eligible voters is Poisson distributed with parameter n, which represents the mean number of eligible voters. The distribution of preferences of these voters, of course, depends on the

[3] Shayo and Harel (2012) simulate somewhat large elections by using a lottery whereby, with probability p the outcome chosen by the subject is picked and with probability $1-p$ the computer picks the outcome. When the computer picks, the weights between the two outcomes are determined according to an equilibrium of some voting model. This design has the important advantage that is does not require a large number of subjects interacting with one another to produce the pivot probabilities of a large election. Moreover, the design allows the experimenter to directly control beliefs about pivotality. A key drawback of this approach is that the probability of being pivotal is no longer subjective, as it is in the field. Many studies, dating back to Allais (1953), demonstrated substantial differences in choice behavior when individuals face events with subjective versus objective probabilities. An important difference between our study versus Shayo and Harel (2012) is that our experimental manipulations are on subjective beliefs rather than objective beliefs.

[4] Blais and Young (1999) conduct an experiment where they randomly teach some students about the "paradox of voting," finding that the experiment by 7 percentage points. However, they interpret their results as operating by affecting respondents' sense of duty.

[5] Examples include recent papers by Malmendier and Nagel (2012), Barseghyan et al. (2012), Goettler and Clay (2011), Grubb and Osborne (2011), and Hoffman and Burks (2012). DellaVigna (2009) provides a survey of earlier work.

realized state, which we assume takes on two possible values, $\theta \in \{\theta_l, \theta_h\}$ where $0 < \theta_l < \frac{1}{2} < \theta_h < 1$. In addition, voters differ in their costs of voting. We assume that each voter i has a cost c_i, drawn from a uniform distribution on $[0, 1]$, where we scale the valuations so as to ensure interior solutions.[6]

A voter will choose to participate if and only if her costs are smaller than her expected benefit from voting. The benefit from voting is merely the strength of preference multiplied by the chance of casting a decisive vote conditional on the voter's information. Hence, in any equilibrium, the cost threshold (equivalently the probability) that an A type voter participates is given by

$$p_A = v_A \Pr\left[Piv_A | A\right]$$

Here, the expression Piv_A denotes the set of events where an additional vote for A proves decisive; that is, the set of events where the vote is either tied or where candidate A is behind by one vote. The conditioning factor denotes the fact that, since a voter's preference is A, this is informative about the state and hence about the likely voting behavior of others, which determines the chance of casting a decisive vote. Likewise, for voters favoring B, we have

$$p_B = v_B \Pr\left[Piv_B | B\right]$$

Thus, an equilibrium induces an ex ante probability $\sigma_{A\theta}$ that a voter will choose A in state θ and an ex ante probability $\sigma_{B\theta}$ that a voter will choose B. Because abstention is allowed, it will typically be the case that $\sigma_{A\theta} + \sigma_{B\theta} < 1$.

So far, the model is entirely standard and identical to Krishna and Morgan (2013). We depart from the standard model in the following way: Voters process the data generating process producing outcomes differently depending on their probabilistic sophistication. With probability $1 - \gamma$, a voter acts as a true Bayesian while with complementary probability, the voter acts as a non-believer in the law of large numbers (NBLLN).

Let λ denote the true probability that $\theta = \theta_l$.In addition to differing in their preferences over candidates, voters also differ in their strategic sophistication. Some voters act as true Bayesians and determine likely voting outcomes in the standard way while others suffer from a non belief in the law of large numbers (NBLLN). These voters view the data generating process as follows: When the voting process is generated by $(\sigma_{A\theta}, \sigma_{B\theta})$, an NBLLN believes that it is generated via a multinomial process with parameters (β_A, β_B) where β_i denotes the ex ante probability that a vote is cast for candidate i. The values of β_A, β_B are drawn from some density $f(\beta_A, \beta_B | \sigma_{A\theta}, \sigma_{B\theta})$ satisfying the following assumptions, which are analogous to $A1$ through $A5$ in BRR.

Assumptions

1. f is absolutely cts in β, full support in unit simplex, and cts in σ.
2. Likelihood ratio: For all $\sigma_{A\theta} < \sigma'_{A\theta}$, $\frac{f(\beta_A, \beta_B | \sigma'_{A\theta}, \sigma_{B\theta})}{f(\beta_A, \beta_B | \sigma_{A\theta}, \sigma_{B\theta})}$ is increasing in β_A and likewise for $\sigma_{B\theta}$.

[6]The assumption of uniform costs merely allows for the direct calculation of the probability of voting from the cost threshold. In large elections, only voters with the lowest costs will participate and hence, the relevant cost distribution will be approximately uniform in the limit; hence, the assumption is without loss of generality in large elections.

3. For all $(\sigma_{A\theta}, \sigma_{B\theta})$, $E[\beta_A|\sigma_{A\theta}, \sigma_{B\theta}] = \sigma_{A\theta}$ and $E[\beta_B|\sigma_{A\theta}, \sigma_{B\theta}] = \sigma_{B\theta}$.

4. Suppose, wlog $\sigma_{A\theta} > \sigma_{B\theta}$, then for every (β_A, β_B) such that $\beta_A < \beta_B$, $f(\beta_A, \beta_B|\sigma_{A\theta}, \sigma_{B\theta}) > f(\beta_B, \beta_A|\sigma_{A\theta}, \sigma_{B\theta})$.

The first assumption merely ensures that the distribution of beliefs for NBLLN types is well-behaved mathematically. The second assumption indicates that, when participation rates for A voters (say) are higher, the belief process for NBLLN types places greater weight (in the likelihood sense) on higher β_A realizations and similarly for higher particiaption by B voters. The third assumption requires that the beliefs of NBLLN types are, on average, correct in the sense that the average participation of A and B voters corresponds to the true underlying voting process. The last assumption ensures that greater weight is placed on a given expected vote realization when it is consistent with the underlying vote share than its "twin" with the opposite expected vote realization that is inconsistent.

The individual voter is unaware of the exact realization (β_A, β_B) and therefore computes her chance of being pivotal based on the distribution of possible realizations. For clarity in distinguishing the formation of pivotal probabilities by NBLLN types versus Bayesian types, we shall use the expression $\mathcal{P}[\cdot]$ to denote the probability of a pivotal event computed from the perspective of an NBLLN and $\Pr[\cdot]$ for the probability as computed by a Bayesian. Similarly, we will use the expression π_A (resp. π_B) to denote the participation rate (probability) of an NBLLN and p_A (resp. p_B) for a Bayesian.

The underlying idea is that non-believers in the law of large numbers perceive greater dispersion in voting outcomes than would be produced from the true data generating process. Essentially, they exclude the possibility that, as the number of draws becomes large, all probability will concentrate near the mean outcomes of the random variable in question. There is, by now, a vast experimental literature, which we add to in this paper, showing this to be behaviorally descriptive.

To close the model, an equilibrium is described by beliefs (and implied participation rates) $(\sigma_{A\theta}, \sigma_{B\theta})$, which denote the ex ante turnout rates for A and B voters in state θ. In equilibrium, all types will hold correct and identical beliefs about this primitive (though they may differ in the probabilities ascribed to a given state). Moreover, these beliefs satisfy the participation equations, weighted across types. That is, an equilibrium satisfies:

$$
\begin{aligned}
\sigma_{A\theta} &= \theta\left(\gamma\pi_A + (1-\gamma)\, p_A\right) \\
\sigma_{B\theta} &= (1-\theta)\left(\gamma\pi_B + (1-\gamma)\, p_B\right) \\
p_A &= v_A \Pr[Piv_A|A] \\
p_B &= v_B \Pr[Piv_B|B] \\
\pi_A &= v_A \mathcal{P}[Piv_A|A] \\
\pi_B &= v_B \mathcal{P}[Piv_B|B]
\end{aligned}
$$

Proposition 1: *An equilibrium exists. Furthermore, in any equilibrium, both A and B voters* *participate at strictly positive rates less than one.*

3 Analysis

We are now in a position to analyze equilibrium participation and election outcomes. To begin with, suppose that there is only a single state $\theta \neq 1/2$. We will call an election ϵ-percent close if the margin of victory (in terms of percent) is less than ϵ. We will call an election ι-vote close is the margin of victory (in terms of number of votes) is less than ι.

Proposition 1 shows that although a Bayesian believes that for appropriately large elections in states where voters are sufficiently partisan, there is a negligible chance of the election being close. However, a NBLLN, regardless of the size of the election, or the partisanship of the electorate, always believes that probability of a close elections will not be below some strictly positive value. This of course, immediately implies that for large elections, and sufficiently partisan electorates, a NBLLN will always believe a close election is more likely than a Bayesian.[7]

To begin, we state a fairly standard result in the voting literature pertaining to the "underdog principle," which notes that votes cast for the side with the smaller expected vote share are more likely to be pivotal than votes cast for the side with the higher expected vote share. The result is intuitive: Since votes are pivotal only in the event of a tie or the event where a given side is behind by one vote, then votes for the side with the smaller vote share, which is more likely to be behind in the election, are hence more likely to be decisive. While this result is known for voters with Bayesian beliefs, we establish it for NBLLN types below.

Lemma 1: *Suppose* $\sigma_A < \sigma_B$, *then* $\mathcal{P}\left[Piv_A\right] > \mathcal{P}\left[Piv_B\right].$

From Krishna and Morgan (2013), we know that the result holds for any fixed voting profile (σ_A, σ_B). Furthermore, for any expected vote realization (β_A, β_B) it is the case that

$$\Pr\left[Piv_A|\left(\beta_A,\beta_B\right)\right] - \Pr\left[Piv_B|\left(\beta_A,\beta_B\right)\right] = \Pr\left[Piv_B|\left(\beta_B,\beta_A\right)\right] - \Pr\left[Piv_A|\left(\beta_B,\beta_A\right)\right]$$

Finally, assumption 4 guarantees that for all $\beta_A < \beta_B$, we have

$$\begin{aligned} &f\left(\beta_A,\beta_B|\sigma_A,\sigma_B\right)\left(\Pr\left[Piv_A|\left(\beta_A,\beta_B\right)\right] - \Pr\left[Piv_B|\left(\beta_A,\beta_B\right)\right]\right) \\ &> f\left(\beta_B,\beta_A|\sigma_A,\sigma_B\right)\left(\Pr\left[Piv_B|\left(\beta_B,\beta_A\right)\right] - \Pr\left[Piv_A|\left(\beta_B,\beta_A\right)\right]\right) \end{aligned}$$

[7] Mandler (2012) generates similar outcomes in a model with aggregate uncertainty. However, that model will fail to explain the lack of updating from large polls that we discuss in the following sub-section.

which, by integrating over all $\beta_A < \beta_B$, we obtain

$$\mathcal{P}\left[Piv_A\right] - \mathcal{P}\left[Piv_B\right] =$$
$$\int_{\beta_A}\int_{\beta_B<\beta_A} \left(\left(f\left(\beta_A, \beta_B|\sigma_A, \sigma_B\right) - f\left(\beta_B, \beta_A|\sigma_A, \sigma_B\right)\right)\left(\Pr\left[Piv_A|\left(\beta_A, \beta_B\right)\right] - \Pr\left[Piv_B|\left(\beta_A, \beta_B\right)\right]\right)\right) d\beta_B d\beta_A$$
$$> 0$$

Using Lemma 1, we may immediately deduce (assuming that the pivot probabilities go to zero):

Proposition 2: *For all γ, all voting equilibria in large elections are utilitarian. That is, the candidate favored by a social planner placing equal weight on all voters wins with probability going to one as the size of the electorate grows unbounded.*

Next, we examine the chances of close elections, defined both in levels and as percentages, as the electorate grows large. Define an ϵ percent close election as one in which $\frac{\sigma_A}{\sigma_B} \in (1-\varepsilon, 1+\varepsilon)$. Suppose that $\frac{\theta v_A}{(1-\theta)v_B}$ is sufficiently far from 1/2 in either direction that, for any sequence of equilibria $(\sigma_{A,n}, \sigma_{B,n})$ every subsequence has the property that $\lim_{n\to\infty}\frac{\sigma_A^*}{\sigma_B^*} \notin (1-\varepsilon, 1+\varepsilon)$.[8]

Definition: *say that welfare is ε away from 1/2 if for any sequence of equilibria $(\sigma_{A,n}, \sigma_{B,n})$ every subsequence has the property that $\lim_{n\to\infty}\frac{\sigma_{A,n}}{\sigma_{B,n}} \notin [1-\varepsilon, 1+\varepsilon]$. Define the* closest *convergent subsequence (if one exists) to be $\left(\sigma_{A,n}^{\min}, \sigma_{B,n}^{\min}\right) \to \left(\sigma_{A,n}^*, \sigma_{B,n}^*\right)$ satisfying* $\liminf\left(\left|\frac{\sigma_{A,n}^{\min}}{\sigma_{B,n}^{\min}} - \frac{1}{2}\right|\right)$*; that is, $\frac{\sigma_{A,n}^*}{\sigma_{B,n}^*}$ is the convergent sequence that is closest to a 50-50 vote share ratio. Note that when $(\sigma_{A,n}, \sigma_{B,n})$ has no convergent subsequences, then welfare is ε away from 1/2 trivially.*

We are no win a position to compare beliefs about close elections across individuals.

Proposition 3: *Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that welfare is ε away from 1/2. Then,*

1. *For all $\zeta \in (0,1)$, there exists an n' such that, for all $n > n'$, in every subsequence, Bayesians estimate the chance of an 2ε percent close election as being less than ζ.*

2. *There exists $\xi^* \in (0,1)$, there exists an n'' such that, for all $n > n''$, NBLLNs estimate the chance of a 2ε percent close election as being greater than ξ^* in every convergent subsequence.*

To gain intuition for the previous proposition, first consider a setting where all voters are Bayesian, i.e. $\gamma = 0$. Here, the model is identical to Krishna and Morgan (2013) who showed that the candidate which satisfies the utilitarian criterion is elected with probability going to 1 in a large election. Furthermore, the vote difference, ι becomes arbitrarily large in the limit Furthermore, the margin of victory is bounded away from 1/2 in large elections. To see this, recall that the equilibrium

[8] The proof of Proposition 2 implies that there exists a proportional mapping between the limit vote share ratio and the welfare ratio such that, as the welfare ratio favors one side by greater amounts, so too does the limiting vote share ratio. The exact mapping is not easily expressed in closed form.

conditions may be expressed as

$$\frac{n\theta p_A}{n(1-\theta)p_B} = \frac{\theta v_A}{(1-\theta)v_B}\frac{\Pr[Piv_A]}{\Pr[Piv_B]}$$

where the conditioning on states and preferences is omitted because there is no aggregate uncertainty. In large elections, it is known that $p_A, p_B \to 0$ at the same rate. Moreover, $\Pr[Piv_A], \Pr[Piv_B] \to 0$ at the same rate as well. Finally, if $\Pr[Piv_A] < \Pr[Piv_B]$ iff $\theta p_A > (1-\theta)p_B$. The margin of victory $\iota = n(\theta p_A - (1-\theta)p_B) \to \infty$ since $np_A, np_B \to \infty$, and at the same rate, and $\theta \neq 1/2$. The vote percentage converges to ???, which is not equal to 1/2.

Next, consider the situation when $\gamma = 1$. The equilibrium conditions are identical save for the computation of $\Pr[Piv_i]$, which is determined using (β_A, β_B). To make this distinction clear, we will write $\mathcal{P}[Piv_A]$ to describe the pivot probability as computed by an NBLLN and $\Pr[Piv_A]$ to describe the pivot probability of a true Bayesian. The following observation is immediate: For a given (σ_A, σ_B) and n sufficiently large:

$$\Pr[Piv_A] < \mathcal{P}[Piv_A]$$

and therefore, for any given (large) election, turnout is greater for NBLLNs than for Bayesians.

When there are a mixture of types, then the equilibrium conditions average over both types beliefs. The previous proposition implies that for large enough elections, NBLLNs have a higher beliefs that they will be pivotal than Bayesians.

Corollary 1: *Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that welfare is ε away from 1/2. Then there exists an n' such that for all $n > n'$, NBLLNs assign a higher probability to a 2ε percent close election than Bayesians for every convergence subsequence.*

However, in contrast to the previous proposition, if the electorate is not very partisan (e.g. $\theta = .5$) then a NBLLN can underestimate the probability of a close election. This is because if the electorate is not very partisan then close elections are the expected mean outcome. A NBLLN overestimates extreme outcomes, and underestimates the probability of the mean outcome.

Of course, in elections what really matters is not the percent difference between the candidates, but the vote difference between candidates. Recall that an ι vote close election is an election that is decided by less than ι votes. Although a NBLLN believes that ϵ-percent close elections are always possible, he, like a Bayesian, does not believe this is true for ι-vote close elections. This is simply because as the electorate gets larger and larger, the same *iota*-vote close elections requires a closer and closer percentage ϵ to achieve. However, a NBLLN still believes ι-vote close elections are more likely than a Bayesian for large partisan elections. This is because a NBLLN overestimates the likelihood of any ϵ-percentage election.

Proposition 4: *Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that the welfare ratio is not equal to 1/2. Then for all $\zeta \in (0,1), \iota > 0$ there exists an n' such that, for all $n > n'$, in every subsequence, Bayesians and NBLLNs estimate the chance of an 2ε percent close election as being less* *than ζ. However, there exists an n'' such that for all $n > n''$, NBLLNs assign a higher probability to an ι vote close election than Bayesians for every convergence subsequence.*

Despite their difference in the level of probability they assign to close elections, both a NBLLN and a Bayesian respond in similar ways to changes in the partisanship of the electorate.[9]

Proposition 5: *Fix n and consider two possible equilibria voting probability ratios $\frac{\sigma_A}{\sigma_B} > \frac{\sigma_A^{'}}{\sigma_B^{'}} > 1$ then both Bayesians and NBLLNs believe that that the probability of either an ϵ or ι close election is higher in the equilibrium defined by $\frac{\sigma_A}{\sigma_B}$ than the equilibrium defined by $\frac{\sigma_A^{'}}{\sigma_B^{'}}$.*

Of course, the assumption of a single, known state is extreme. It is more natural to assume that the agent has a set of possible states (i.e. values of θ), including a countably infinite number. Not all of the results naturally extend. A Bayesian will now believe, given some sets of priors, that even from with an infinite voting population, that a close election is always possible. However, given large enough polls that are extreme enough, a Bayesian will cease to believe in the possibility of close elections. This will not happen with a NBLLN. So long a sufficient weight (in terms of prior probabilities) are assigned to extreme states of the world (i.e. states sufficiently far from .5) a NBLLN will continue to overestimate the probability of a close election relative to a Bayesian.

3.1 Polls and Updating

We will now assume there are two possible states θ_1, θ_2.[10] There is a common prior over the states: $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$ with $f_\Theta(\theta_1) + f_\Theta(\theta_2) = 1$. We will assume without loss of generality in this section that $theta_1$ is the true state.

We will think of a poll as providing information about the level of support for each candidate. However, in order to maintain tractability, we will make an assumption in order so that it also does not provide information about the realized size of the electorate. We will assume that a poll is a random sample of individuals who plan on participating in the election. We will assume that after the poll is taken, that the number of participants in the election is re-drawn.

Moreover, to simplify exposition, we will assume that any individual who observes the poll believes it is shown only to them, so that no one elses' beliefs are changed as a result.[11]

Individuals will observe the results of a poll, and then update their beliefs about the state of the world. A Bayesian, given a large enough poll, regardless of the size of the electorate, will learn the true voting probabilities σ_i arbitrarily well, and given a large enough expected electorate (the Poisson parameter n), this will map into an underlying state θ_1 or θ_2. On the other hand, given a poll that asymptotically reflects the underlying population, a NBLLN has an upper bound on the amount he can learn from any poll.[12] Therefore, with a sufficiently large poll, a NBLLN will infer

[9] Obviously the reverse of Proposition 5, where the states are less than .5, is also true.

[10] The results easily generalize to more than just two states.

[11] Similar results to ours can be derived in the more complicated frameworks where either individuals believe the polls are common knowledge, or most realistically, where it is common knowledge that each individual has a certain probability of observing the results of the poll.

[12] Where the polls samples from the population without replacement, then obviously a NBLLN will learn the true state for sure if he observes the entire finite population.

less than a Bayesian from large enough polls.[13]

Proposition 6: *Suppose θ_1 is the true state, and assume that polls are random samples from a population. Fix $\theta_1, \theta_2 \neq .5$, all $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$, and $0 < \zeta < 1$. Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$.*

1. *For all $\tau > 0$, there exists an N' such that for all convergent subsequences and all $N > N'$, where the realization of the electorate size is greater than N, and the poll is of size N, then the probability that that a Bayesian assigns probability less than ζ to θ_2 being the true state is less than τ.*

2. *For all $\zeta > 0$ and $\tau < 1$, for all convergent subsequences and all N, such that the realization of the electorate size is greater than N, and the poll is of size N, then with probability τ the posterior probability that a NBLLN assigns to θ_2 being the true state is greater than ζ for all N.*

3. *For all $\tau < 1$ there exists an N' such that for all convergent subsequences and all $N > N'$, where the realization of the electorate size is greater than N, and the poll is of size N, a NBLLN places a higher posterior on θ_2 being the true state compared to a Bayesian with probability greater than τ.*

Of course, a NBLLN and a Bayesian are both sensitive to the sample size and population size — fixing a sample size N, they both infer less about a larger finite population, and fixing a population size, they infer more about it as the sample size grows.[14,15] In many situations observing a poll that predicts a close margin of victory, instead of a poll that predicts a large margin, will lead to the decision-maker's posterior ratio will place a higher weight on a close margin of victory relative to a large margin of victory. However, this only occurs in situations where both possible states, and both poll results, all agree on which candidate is favored. It is a direct implication of the following proposition.

Proposition 7: *Fix all parameters and an equilibrium, as well as two polls, P_1 and P_2. Assume that the proportion of individuals voting for A in P_1 is larger than in P_2. If either a NBLLN or a Bayesian sees P_1 they will place a higher posterior probability on θ_1 than if they see P_2.*

Of course, if the states or the poll results are on either side of .5, then it could be the case that observing a more extreme poll leads to a higher posterior on the closer state. For example, imagine

[13] Of course, there could be alternative behavioral explanations for why individual's do not update much based on a poll. For example, they could believe in the Law of Large Numbers, but not be sure whether he has seen the information before. However, this type of a model would still fail to predict that individuals would over-estimate the probability of a close election.

[14] We do not formalize these intuitions as the subjects in our experiment were not directly informed of the survey size, so we have no way to control for that in a regression. Furthermore, it would require us to consider a slightly different framework, sampling without replacement, from a finite sample.

[15] If we instead assume that a poll is a sample without replacement of voters, there are additional comparisons that can be done. For small polls, a NBLLN believes that the marginal benefit of an additional observation is smaller than a Bayesian. But for large polls (i.e. those close enough to the full population), then the marginal benefit of an additional observation is bigger for a NBLLN than for a Bayesian.

that priors are equal, $\theta_1 = .7, \theta_2 = .48$, the proportion of A voters in P_1 is .48 and the proportion of A voters in P_2 is .2. In this case, if an individual observes P_2 they find state 2 (the closer state) more likely relative to if they had observed P_1, even though P_2 is the more extreme poll.

One way to pull apart non-belief in the law of large numbers from competing explanations (such as aggregate uncertainty) is by looking at beliefs in close elections after large polls. After large polls, a Bayesian should be almost certain about the state, and so for a sufficiently partisan population, should believe that in a large election, the probability of a close election is negligible. Even after a large poll, a NBLLN will still be uncertain about the state, and always believe that there is a non-negligible chance of a ϵ-percentage close election.

Proposition 8: *Suppose θ_1 is the true state, and assume that polls are random samples from a population. Fix $\theta_1, \theta_2 \neq .5$, all $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$, and $0 < \zeta < 1$. Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that welfare is ε away from 1/2.*

1. *For all $\zeta > 0$, there exists an N' such that for all convergent subsequences and all $N > N'$, where the realization of the electorate size is greater than N, and the poll is of size N, Bayesians estimate the chance of an 2ε percent close election as being less than ζ after observing a poll.*

2. *There exists $\xi^* \in (0, 1)$, such that for all convergent subsequences and all N, where the realization of the electorate size is greater than N, and the poll is of size N, NBLLNs estimate the chance of a 2ε percent close election as being greater than ξ^*.*

3.2 Voting

The previous propositions have examined beliefs about pivotality and election outcomes across Bayesians and NBLLNs. This section will consider the behavior of agents — when they vote. First, agents of all types will be more likely to vote if they have a higher probability of being pivotal — as it is more likely the benefits of voting exceed the randomly drawn cost of voting.

Proposition 9: *Fix parameters and an equilibrium. An individual with a higher probability of being pivotal will have a higher probability of voting.*

Of course, all else being equal, we would expect individuals who were shown polls with a smaller margin of victory to have beliefs that they are more likely to be pivotal, and so they should be more likely to vote. The change in the probability of voting caused by the treatment can be written as:

Proposition 10: *Suppose θ_1 is the true state, and assume that polls are random samples from a population. Fix $\theta_1, \theta_2 \neq .5$, all $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$ and an equilibria $(\sigma_A, \sigma_B)_n$. Fix a type (Bayesian or NBLLN). Then if a poll has smaller margin of victory an individual observing that poll will have a higher probability of voting.*

Because NBLLN believe an election is more likely to be close, then all else being equal, they will tend to vote more.

Proposition 11: *Suppose θ_1 is the true state, and assume that polls are random samples from a population. Fix $\theta_1, \theta_2 \neq .5$, all $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$, and $0 < \zeta < 1$. Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that welfare is ε away from 1/2.*

1. *There exists an n' such that for all $n > n'$, NBLLNs are more likely to vote than Bayesians for every convergence subsequence.*

2. *There exists an N' such that for all convergent subsequences and all $N > N'$, where the realization of the electorate size is greater than N, and the poll is of size N NBLLNs are more likley to vote than Bayesians for every convergence subsequence after observing a random poll.*

3.3 Summary of Claims

This sub-section summarizes the implications of non-belief in the Law of Large Numbers in the our simple model of elections that we will test in the data set.

1. NBLLNs will overestimate the probability of close elections in sufficiently partisan elections relative to Bayesians (Corollary 1 and Proposition 4)

2. Individuals who believe the mean electoral outcome is farther from .5 believe that close elections are less likely (Proposition 5)

3. NBLLNs will update less from poll outcomes than true Bayesians (Proposition 6)

4. Individuals who observe a poll more in favor of candidate A will update their beliefs more in the direction of candidate A winning the election than if they observe a poll less in favor of candidate A (Proposition 7)

5. NBLLNs who observe sufficiently partisan large polls will believe that elections are more likely to be close compared to Bayesians who observe the same poll (Proposition 8)

6. Individuals who place a higher probability on a close election should be more likely to vote (Proposition 9)

7. Individuals who are shown a poll with a closer margin of victory should be more likely to vote (Proposition 10)

8. NBLLNs should be more likely to vote than Bayesians (Proposition 11)

4 Methods and Data

We test the theory using our field experiment with 16,000 voters and describe the design of the experiment below.

4.1 Experimental Sample

We focused on states with gubernatorial races. In each state selected, we used all the respondents in the Knowledge Networks KnowledgePanel who were registered voters. We obtained poll information from the websites FiveThirtyEight.com and RealClearPolitics.com.

In choosing our sample of states, we excluded Colorado, Massachusetts, Maine, Minnesota, and Rhode Island, as these were states where there was a major third party candidate. In addition, we restricted our sample to states (1) where the was a poll within the last 30 days indicating a vote margin between the Democrat and Republican candidates of 6 percentage points or less and (2) where there were two polls that differed between each other by 4 percentage points or more. This left us with 13 states: California, Connecticut, Florida, Georgia, Illinois, Maryland, New Hampshire, New York, Ohio, Oregon, Pennsylvania, Texas, and Wisconsin.

4.2 First Survey

The first survey was sent out to subjects on October 19th, 2012, which was two weeks before the election. The survey was administered by Knowledge Networks, a large online survey company. The subjects were participants in the Knowledge Networks KnowledgePanel, a weekly online national survey.

The timing for the first survey was as follows (screen shots with exact question wording are given in the Appendix):

1. Subjects received an explanation of stating probabilities
2. Subjects answered political knowledge and interest questions
3. Subjects stated their predicted vote margin, the probability of a close election, and their probability of turning out and voting for particular candidates
4. Information treatment
5. Subjects stated their predicted vote margin, the probability of a close election, and their probability of turning out and voting for particular candidates

The survey began with a standard "explanation of probabilities" developed in the pioneering working of Charles Manski and used in Delavande and Manski (2010), followed by several questions on subjects' political knowledge and interest. We then asked subjects about their prediction of the vote margin, the chance the election would be decided by less than 100 or 1,000 votes,[16] the chance that they would vote, and their chance of voting for the different candidates. We decided to ask subjects about the event of the election being decided by less than 100 or 1,000 votes instead of the outright event of being pivotal, as some political scientists and psychologists we spoke to believed that

[16]To avoid any issues of anchoring or voters trying to make their answers consistent across questions, voters were randomly assigned to be asked about *either* the chance the election would be decided by less than 100 *or* less than 1,000 votes.

such questions would be easier for subjects to comprehend.[17] All belief questions were administered without any incentives for accuracy.[18] We then provided the information treatment, described below. Immediately after the information treatment, subjects were asked the same questions again. We decided to ask the same questions immediately after treatment so as to detect if there was any immediate impact on voting intentions. Given that the time before an election is often filled with significant information in the news media, we wanted to give our treatment the best possible chance of having an impact of on voting intentions.

On the Friday before the election (October 29th), we went out a reminder email to subjects containing the first set of polls that they were treated with.

4.3 Selection of Polls and Information Treatment

Poll choices were finalized on October 17th, 2010. To select the polls, we located the poll over the 40 days prior to the start of the experiment (which started October 19th) with the greatest margin between the Democrat and Republican candidates. This served as our not close poll. We then selected the poll that was most close, conditional on the same candidates being ahead and behind. If two polls were tied for being least close or most close, we selected the poll that was most recent.

In the experiment, the language we used to present the poll was as follows:

Below are the results of a recent poll about the race for governor. The poll was conducted over-the-phone by a leading professional polling organization. People were interviewed from all over the state, and the poll was designed to be both non-partisan and representative of the voting population. Polls such as these are often used in forecasting election results. Of people supporting either the Democratic or Republican candidates, the percent supporting each of the candidates were:

Jerry Brown (Democrat): 50%

Meg Whitman (Republican): 50%

That is, poll numbers were calculated using the share of poll respondents favoring the Democratic of Republican candidates. The number we gave for the Democrat was equal to 100 * Percent Dem / (Percent Dem + Percent Reb).

4.4 Post-election survey, Voting data, and Coins Experiment

The post-election survey was sent out on November 19th, 2010, 17 days after the election, and subjects completed the survey until November 30th, 2010. Subject completed the coins experiment

[17]In addition, as emphasized by Mulligan and Hunter (2003), vote totals within some range of an exact tie often trigger recounts in U.S. elections; elections are then oftentimes decided by courts (e.g. recall the 2000 Presidential Election in Florida). Thus, it is likely accurate to think of having an election decided by less than 100 votes means that your vote has a 1 in 100 chance of being pivotal.

[18]We decided not to use incentives for accuracy after a political scientist colleague informed us that doing so may be illegal, possibly constituting either gambling on elections or potentially even being a form of paying people to vote (for the question where ask people about their intended voting probability). Field experiments that have randomized incentives for accuracy often find little impact of using incentives on beliefs (Hoffman and Burks, 2012). Given the wide range of backgrounds, ages, and education levels in our sample, we suspect that adding financial incentives for accuracy via a quadratic scoring rule might have actually increased elicitation error due to additional complexity instead of decreasing it.

measuring non-belief in the law of large numbers. We then asked subjects whether they voted and whom they voted for.

We obtained administrative voting data on the voters in the sample for the last 10 years. We worked with a "voting validation firm" that collects administrative voting records from the Secretaries of State in different U.S. states.

The coins experiment is from Benjamin et al. (2012a), which is based on Kahneman and Tversky (1972). Subjects were asked the following question: "Imagine you had a fair coin that was flipped 1,000 times. What do you think is the percent chance that you would get the following number of heads." Subjects typed in a number corresponding to a percentage in each of the following bins: 0-200 heads, 201-400 heads, 401-480 heads, 481-519 heads, 520-599 heads, 600-799 heads, 800-1,000 heads.

5 Experimental Results

Before testing the theory, we verify in Table 2 that the randomization was successful. Across most variables, the Close Poll group, No Close Poll group and Control group have similar characteristics. Exceptions are that voters in the Not Close group had a slightly higher *ex ante* belief that the election would be decided by less than 100 votes (but not for less than 1,000 votes or Predicted Margin) and that voters in the Control group were more likely to vote in previous elections than voters in the Close or Not Close groups. We thus control for ex ante perceived probability of less than 100 votes or shared voted in previous elections in the analysis.

5.1 Beliefs and Updating

We first examine the subjects beliefs about close elections. In Figure 2, we show that voters systematically overpredict the probability of a very close election. There is a large amount of mass around 0, 1, or 2 percent, with many voters predicting that a very close election is unlikely. However, there is also a large mass of voters who are not 2 percent or less. Similar patterns are observed in Figure 3, which is restricted to voters with Master's or PhD degrees. Here, the median belief is smaller, but still quite high on average. These results support Claim 1, as the probability of an election being decided by less than 1000 votes even in the smallest state in our sample (New Hampshire) is less than 1%.[19] Historically, there have been very few recent gubernatorial elections decided by less than 100 or 1,000 votes. Since 1950, there have been 7 gubernatorial elections decided by less than 1,000 votes (Rhode Island in 1956; Vermont in 1958; Maine, Minnesota, and Rhode Island in 1962; Maine in 1970; and Washington in 2004) and only 1 gubernatorial election decided by less than 100 votes (Minnesota in 1962). Of the 813 contested gubernatorial elections since 1950, the shares with

[19] Myatt (2011) provides a model capable of rationalizing sizeable turnout, where the probability of being pivotal is on the order of $\frac{40}{N}$. For a small state with 1 million people, and say 300,000 voters in a gubernatorial election, this would correspond to a 1 in 7,500 chance of being pivotal. For a large state with 10 million people, this would correspond to a 1 in 75,000 chance of being pivotal. However, believing that the chance of the election being decided by less than 100 votes is 10% corresponds to believing the probability of being pivotal is roughly 1 in 1,000, indicating overestimation by 1-2 orders of magnitude.

margins less than 1,000 and 100 votes were about 1% and 0.1%, respectively (and 0.1% and 0% after 1970).

While beliefs are very high, Table 3 shows that beliefs vary with expected predictors. In particular, the actual vote margin in a state is a strong predictor of the perceived vote margin, as well as the perceived probability the election will be decided by less than 100 or 1,000 votes.

In addition, Table 3 shows that voters with greater NBLLN are more likely to overestimate the probability of a very close election. Voters who believed that the probability of getting outside of 481-519 Heads on 1,000 coin flips is higher are much more likely to report high perceived probabilities of being pivotal. This result holds controlling for educational level, income, and other controls.

Turning next to the updating of beliefs by our subjects, Table 4 provides simple non-parametric evidence that voters updated in response to the experimental poll information. It tabulates whether votes increase, decrease, or did not change their beliefs, showing impacts on predicted vote margin, probability decided by less than 100 votes, and probability decided by less than 1,000 votes. The poll information was given to them in terms of vote margin, so it is perhaps unsurprising that voters would update on this metric, but there is also clear updating on less than 100 or 1,000 vote margins. Consider, for example, the probability the election would be decided by less than 1,000 votes. Of voters in the Close Poll treatment, 10% decrease their beliefs, 65% did not change them, and 24% increase their beliefs, whereas for voters in the Not Close Poll treatment, 18% decrease their beliefs, 67% do not change them, and 14% increase their beliefs. Many voters are not changing their beliefs at all. However, for the share that do, more do so in the expected direction. The lack of updating is in line with Claim 3. Furthermore, the broad patterns of updating are also consistent with Claim 5.

Tables 5 and 6 confirms the same result as in Table 4 using a regression with controls:

$$b_{i,post} = \alpha_0 + \alpha_1 T_i + X_i \beta + \epsilon_i \tag{1}$$

where $b_{i,post}$ is person i's post-treatment belief about the closeness, T_i is their randomized treatment status, X_i is controls, and ϵ_i is an error. Tables 5 uses predicted vote margin for b whereas Table 6 analyzes probability election decided by less than 100 or 1,000 votes. In addition to $b_{i,post}$ as the dependent variable, we can also look at changes in beliefs across people, estimating:

$$\Delta b_i = \alpha_0 + \alpha_1 T_i + \Delta \epsilon_i \tag{2}$$

Panel A of Table 5 shows that receiving the close treatment leads the average voter to decrease their predicted vote margin by 2.8 percentage points, with similar estimates using $b_{i,post}$ and Δb_i. In addition, consistent with theory, we see that voters who are less informed update more. We measure how informed voters are using their self-expressed interest in politics (1-5 scale), whether they could correctly identify Nancy Pelosi as the Speaker of the House, and the share of the time they voted in the previous 5 elections. For example, a voter who identifies as having very low interest in politics would updated 4.7 percentage points, whereas a voter with a very high interest in politics updated only 1.8 percentage points. In Panel B, we repeat the regressions using a continuous version of the treatment variable, the vote margin in the poll they were assigned (e.g. a 57-43 poll would have a margin of 14 points). Voters update their margin 0.22 points for every 1 point change they see in the polls, with large updates for less informed voters.[20]

Table 6 repeats the analysis for the impact on probability that the vote margin is less than 100 or 1,000 votes. In Panel A, we see that both probabilities increased by about 2.5 percentage points after receiving the close poll treatment.[21] Panel B shows that each additional percentage point drop in the margin in the randomly assigned poll led to 0.14 percentage point increase in the probability of less than 100 or 1,000 votes.

An alternative explanation for our result is that voters do not actually update their beliefs at all, but rather appear to change their beliefs as a result of a Hawthorne Effect, changing their beliefs to please the experimenter. While we cannot fully rule out this possibility, we provide several reasons why we believe it to be unlikely to explain our results. First, we note we that subjects updated strongly both on vote margins, on which they were provided information, and the probability of a very close election, on which they were not provided information. If voters were simply telling the researchers what "they wanted to hear," it is not clear that they would update on both. Second, as noted earlier, the amount of updating is strongly negatively correlated with political information, that is, less informed people update more. A pure Hawthorne effect seems unlikely to deliver this result (unless, of course, for some reason the people who are less informed, controlling for observable characteristics, are also the ones who are more prone to Hawthorne effects).

5.2 Pivotality and Voting

Table 7 regresses turnout on voter beliefs and various characteristics, showing that many standard predictors of turnout are operative in our setting. Older, more educated, and richer people are all more likely to vote. Although our sample is not a random sample from the U.S. population, these basic voting trends suggest that our sample is not especially atypical. In addition, belief measures do not predict turnout, though we emphasize that the belief measures here are endogenous in these regressions for the reasons we discussed in the Introduction (closer elections are often accompanied by other factors such as increased media coverage, campaign spending, and overall discussion).

Table 8 shows IV regressions of turnout on beliefs instrumenting with our experiment, showing that exogenously affected beliefs do not affect turnout:

$$TURNOUT_i = \alpha_0 + \alpha_1 b_{i,post} + X_i\beta + \epsilon_i \quad (3)$$
$$b_{i,post} = a_0 + a_1 T_i + X_i\beta + u_i$$

[20] In Panel B, column 1 has a coefficient of 0.42 whereas once controls are added in column 2, the coefficient shrinks to 0.22. This occurs because states with actual wider vote margins tend to have polls with wider vote margins. Even though our treatment is randomly assigned within state, the level of the poll vote margins is not randomly assigned across states.

[21] Column 1 of Panel A shows an insignificant effect because as discussed earlier in Table 2, it so happened during our randomization that people assigned to the Not Close Poll group happened to have higher initial beliefs of the margin less than 100 votes.

where $TURNOUT_i$ is a dummy for turnout, $b_{i,post}$ is post-treatment beliefs, and T_i is the treatment dummy. We estimate by 2SLS. In column 1, the coefficient of 0.17 means that for every 1 point increase in the believed vote margin (that is, the election becomes *less close*), turnout *increases* by 0.17 percentage points. The standard error of 0.42 leads to a 95% confidence interval of $(-0.67, 1.01)$, meaning we can rule out an effect size smaller than -0.67. Thus, we can rule out that moving from a perceived moderately sized vote margin of 4 percentage points to a perceived close election with a margin of 0 percentage points would increase turnout by more than 2.68 percentage points. As a point of comparison, being in the 35-44 year old age bracket increases turnout by about 20 percentage points relative to the 25-34 year old age bracket. We can thus rule out that the impact of beliefs is anywhere near as important as that of other predictors like age, education, and income. The F-statistic on the excluded instrument varies by specification, but is often around 40, well over the mark of 10 often used to designate weak instruments (Stock et al., 2002).[22]

Tables 9 and 10 show in addition that changes in belief have no impact on intended turnout or on information acquisition. An alternative explanation of our zero impact on turnout result is that while the experiment may have affected voting tendencies, other events may have occurred in the several days before the actual election that would have over-ridden our impact. Since voting intention was asked immediately after treatment, we can observe whether our experiment had any short-run impacts. Using the IV strategy from Table 8, we see that the experiment had no impact on voting intention. Another alternative explanation is that the experiment may have spurned voters in the close poll treatment to acquire more information about the election, for example, to start following all the polls and reading the polls. Such voters might have discovered that we provided them with the most close recent poll, and might discard the information content once they learn this. However, we see no impact of the experiment on voters' self-reported tendency to pay greater attention to the election.[23]

Therefore, although we find support for Claims 1-6, in that individuals beliefs and updating are consistent with a model of NBLLN, we do not find support that they vote in accordance with their (incorrect) beliefs about being pivotal — Claims 7 and 8. This means that even if we accommodate individuals' true beliefs about being pivotal into models of voting, this still does not generate the behavior predicted by pivotal voting models.

6 Structural Estimation

In this section we estimate a structural model of NBLLN. We use the parameterized form of NBLLN introduced by BRR. The subjective rate distribution $f^{\psi}_{ß|\Theta}(\beta|\theta)$ is a beta-distribution:

[22] There are 3 cases where the F-statistic is below 10, columns 4, 7, and 10. Column 4 and 10 involve the post-treatment probability the election is less by 100 votes; as discussed earlier, it is important to control for the pre-treatment belief the election is decided by less than 100 votes because the close and not close groups were slightly uneven in the randomization. In addition, the F-statistic is 6.95 for column 7 looking at the post-election belief the election is decided by less than 1,000 votes.

[23] Self-reported information acquisition was reported by subjects after the election.

$$f^{\psi}_{\text{ß}|\Theta}\left(\beta|\theta\right)=\beta^{\theta\psi-1}\left(1-\beta\right)^{(1-\theta)\psi-1}\frac{\Gamma\left(\psi\right)}{\Gamma\left(\theta\psi\right)\Gamma\left(\left(1-\theta\right)\psi\right)},$$

The one free parameter $0<\psi<\infty$ is the exogenous parameter that governs the degree of NBLLN ($\psi=\infty$ is simply a TB).[24] From Lemma β-1 of BRR we know that a NBLLN believes the probability of observing A_s votes for candidate A in a total number of N votes is:

$$f^{\psi}_{S_N|\Theta}\left(s|\theta_A\right)=\frac{\Gamma\left(\psi\right)}{\Gamma\left(\psi+N\right)}\frac{\Gamma\left(\theta\psi+A_s\right)}{\Gamma\left(\theta\psi\right)}\frac{\Gamma\left(\left(1-\theta\right)\psi+N-A_s\right)}{\Gamma\left(\left(1-\theta\right)\psi\right)}\frac{\Gamma\left(N+1\right)}{\Gamma\left(A_s+1\right)\Gamma\left(N-A_s+1\right)}.$$

By applying Bayes' Rule, a NBLLN's likelihood ratio after observing a poll of N voters, with A_s individuals who will votes for candidate A is:

$$\Pi^{\psi}_{S_N|\Theta\times\Theta}\left(s|\theta_1,\theta_2\right)=\frac{\Gamma\left(\theta_1\psi+A_s\right)}{\Gamma\left(\theta_2\psi+A_s\right)}\frac{\Gamma\left(\left(1-\theta_1\right)\psi+N-A_s\right)}{\Gamma\left(\left(1-\theta_2\right)\psi+N-A_s\right)}\frac{\Gamma\left(\theta_2\psi\right)}{\Gamma\left(\theta_1\psi\right)}\frac{\Gamma\left(\left(1-\theta_2\right)\psi\right)}{\Gamma\left(\left(1-\theta_1\right)\psi\right)}.$$

One potential concern, which we defer discussion of until the final sub-section, is the issue of response bias in the survey. In particular individuals tend to give responses that are focal more often — individuals may round their answers to the nearest salient number, such as those ending in 5 or 0, or in extreme cases, either 0, 50 or 100.

6.1 Data used in Structural Estimation.

Individuals in the survey vary by state. Within each state individuals are assigned to one of 3 possible treatments. Furthermore, we have measurements of beliefs before the treatment and after the treatment. Denote individual i in state s with treatment t (where $t=m$ denotes the most close poll, $t=l$ denotes the least close poll and $t=\emptyset$ denotes the control treatment), at time τ (where $\tau=b$ for before and a for after the treatment).

For each individual we have reported beliefs about the probability of an election being decided by less than 100 and 1000 votes. Furthermore, we have both these probabilities for each individual before the treatment and after the treatment. Denote individual i's belief in state s, with treatment t at time τ that the election will be decided by less than 100 votes the treatment be $\phi^{100}_{i,s,t,\tau}$. Denote the same belief, but for the election being decided by less than 1000 votes before the treatment be $\phi^{1000}_{i,s,t,\tau}$.

We also have data on each individual's belief about the mean margin of victory in the election. Denote the mean margin of victory, by individual i, in state s, with treatment t at time τ as $\rho_{i,s,t,\tau}$.

For each state s we have the margin of victory predicted by each of the two polls m and l — denoted $\omega_{s,m}$ and $\omega_{s.l}$. We also have realized turnout in state s denoted N_s.

For individual level statistics $z_{i,s,t,\tau}$., we denote the average value across individuals at state, treatment, and time levels as $\bar{z}_{s,t,\tau}$. We denote similar averages across other variables in an equivalent

[24] BRR note that this particular functional form has some additional, stronger implications beyond those discussed in the body of their paper. Furthermore, although the beta distribution always has a single interior maximum, it can be u-shaped for particular small values of ψ.

fashion.

6.2 Estimation Strategy and Results

Our basic estimation result estimates a population level mean of ψ. We currently use only a subset of the belief data to do this.[25] In particular, we will use their initial belief about the probability of an election being decided by less than 1000 votes: $\phi^{1000}_{i,s,t,\tau}$. We assume that individuals have a degenerate prior on the state, and that these priors are represented by their belief about the mean margin of victory $\rho_{i,s,t,\tau}$. [26] We furthermore assume that individuals know, ex-ante, the realized turnout in their state N_s. Of course, this leaves only a single data point per individual. Therefore, we aggregate across individuals at the state level. Since we are taking initial beliefs, we restrict $\tau = b$ and also aggregate across treatments (since individuals were randomly assigned). We obtain state level values $\bar{\phi}^{1000}_{s,b}$ and $\rho_{s,b}$.

Given our model of NBLLN, a rate θ, and a number of voters of size N, the probability of of an election being closer than 1000 votes is the sums of $f^{\psi}_{S_N|\Theta}(s|\theta_A)$ between the values of $0.5N - 1000$ and $0.5N + 1000$, or

$$F^{\psi}_{S_N|\Theta}(0.5N + 1000|\theta_A) - F^{\psi}_{S_N|\Theta}(0.5N - 1000|\theta_A)$$

We can substitute in for the CDF of the outcomes using

$$\begin{aligned} F^{\psi}_{S_N|\Theta}(K|\theta_A) &= \sum_{i=0}^{K} f^{\psi}_{S_N|\Theta}(i|\theta_A) \\ &= \sum_{i=0}^{K} \int_0^1 \frac{N!}{i!(N-i)!} \beta^i (1-\beta)^{N-i} \beta^{\theta\psi - 1} (1-\beta)^{(1-\theta)\psi - 1} \frac{\Gamma(\psi)}{\Gamma(\theta\psi)\Gamma((1-\theta)\psi)} d\beta \\ &= \int_0^1 \beta^{\theta\psi - 1} (1-\beta)^{(1-\theta)\psi - 1} \frac{\Gamma(\psi)}{\Gamma(\theta\psi)\Gamma((1-\theta)\psi)} \sum_{i=0}^{K} \frac{N!}{i!(N-i)!} \beta^i (1-\beta)^{N-i} d\beta \end{aligned}$$

Therefore

[25] Please see last subsection for details of how we plan to extend our analysis to individual level estimates using the full set of available data.

[26] This must be false in the sense that it would not allow the subjects to update at all given new information, but we will use it as a simplifying assumption. In ongoing work we let the prior be a distribution.

$$
\begin{aligned}
& F^{\psi}_{S_N|\Theta}\left(0.5N+1000|\theta_A\right) - F^{\psi}_{S_N|\Theta}\left(0.5N-1000|\theta_A\right) \\
= & \int_0^1 \beta^{\theta\psi-1}\left(1-\beta\right)^{(1-\theta)\psi-1} \frac{\Gamma\left(\psi\right)}{\Gamma\left(\theta\psi\right)\Gamma\left(\left(1-\theta\right)\psi\right)} \sum_{i=0}^{0.5N+1000} \frac{N!}{i!(N-i)!}\beta^i(1-\beta)^{N-i} d\beta \\
- & \int_0^1 \beta^{\theta\psi-1}\left(1-\beta\right)^{(1-\theta)\psi-1} \frac{\Gamma\left(\psi\right)}{\Gamma\left(\theta\psi\right)\Gamma\left(\left(1-\theta\right)\psi\right)} \sum_{i=0}^{0.5N-1000} \frac{N!}{i!(N-i)!}\beta^i(1-\beta)^{N-i} d\beta \\
= & \int_0^1 \beta^{\theta\psi-1}\left(1-\beta\right)^{(1-\theta)\psi-1} \frac{\Gamma\left(\psi\right)}{\Gamma\left(\theta\psi\right)\Gamma\left(\left(1-\theta\right)\psi\right)} \\
& \left(\sum_{i=0}^{0.5N+1000} \frac{N!}{i!(N-i)!}\beta^i(1-\beta)^{N-i} - \sum_{i=0}^{0.5N-1000} \frac{N!}{i!(N-i)!}\beta^i(1-\beta)^{N-i}\right) d\beta
\end{aligned}
$$

We will use the normal approximation of the Binomial distribution

$$
\begin{aligned}
& \int_0^1 \beta^{\theta\psi-1}\left(1-\beta\right)^{(1-\theta)\psi-1} \frac{\Gamma\left(\psi\right)}{\Gamma\left(\theta\psi\right)\Gamma\left(\left(1-\theta\right)\psi\right)} \\
& \left(\sum_{i=0}^{0.5N+1000} \frac{N!}{i!(N-i)!}\beta^i(1-\beta)^{N-i} - \sum_{i=0}^{0.5N-1000} \frac{N!}{i!(N-i)!}\beta^i(1-\beta)^{N-i}\right) d\beta \\
\approx & \int_0^1 \beta^{\theta\psi-1}\left(1-\beta\right)^{(1-\theta)\psi-1} \frac{\Gamma\left(\psi\right)}{\Gamma\left(\theta\psi\right)\Gamma\left(\left(1-\theta\right)\psi\right)} \\
& \left(\Phi_{N\beta,N\beta(1-\beta)}(0.5N+1000) - \Phi_{N\beta,N\beta(1-\beta)}(0.5N-1000)\right) d\beta
\end{aligned}
$$

Where $\Phi_{N\beta,N\beta(1-\beta)}$ is the normal pdf for a normal distribution with parameters $N\beta$ and $N\beta(1-\beta)$. Therefore we can estimate the below equation using non-linear least squares or, using overall averages instead of state-level statistics, solve it using a non-linear solver:

$$
\begin{aligned}
\bar{\phi}^{1000}_{s,b} = & \int_0^1 \beta^{\rho_{s,b}\psi-1}\left(1-\beta\right)^{\left(1-\rho_{s,b}\right)\psi-1} \frac{\Gamma\left(\psi\right)}{\Gamma\left(\rho_{s,b}\psi\right)\Gamma\left(\left(1-\rho_{s,b}\right)\psi\right)} \\
& \left(\Phi_{N_s\beta,N_s\beta(1-\beta)}(0.5N_s+1000) - \Phi_{N_s\beta,N_s\beta(1-\beta)}(0.5N_s-1000)\right) d\beta
\end{aligned}
$$

Solving the above equation using a non-linear solver, we obtain a preliminary estimate of ψ of 45. This is larger than the estimates from the experimental literature. However, several caveats are in order. We neglect to accommodate additional known biases (such as extremeness aversion and fat-tailed distributions) which are documented in the literature (see BRR Appendix A). This leads to difficultly in model being able to accurately match the high level of belief individuals place in close elections. Taking the reported beliefs at face value, this would require individuals' subjective sampling distribution $f^{\psi}_{\mathbb{B}|\Theta}\left(\beta|\theta\right)$ to place an extremely large mass of probability quite close to $\beta = .5$ — i.e. nearly 20 percent of the probability mass. This seems calibrationally implausible. Additional biases, such as extremeness aversion and fat-tailed distributions can help alleviate this problem, and also will lead to lower estimates of ψ. That said, there remain some individuals in the sample whose beliefs about close elections will remain difficult to rationalize under any reasonable model — for example those that place upwards of 30 percent likelihood on close elections while still believing the average margin of victory to be greater than 1 percent. This is because those subjects subjective sampling distribution will not be single peaked, and have interior intervals where the support is negligible; distributions which are possible, but seem at odds with the experimental evidence.

6.3 Ongoing Extensions

Our current structural estimation is limited in that it estimates population averages using a single statistic (out of the five we have available). Furthermore, it imposes extremely strong assumptions about the nature of individuals beliefs about the state of the world (i.e. the underlying probability of support for candidate A), in that beliefs are degenerate.

We can once again estimate a parameter ψ_i for each individual. In order to both beliefs about close elections and updating in our estimation using a single theoretical framework, we will have to assume that individual's prior beliefs about the margin of victory in a state are not a point mass (as we currently do) but are rather a distribution — $G(\theta)$. We will parameterize G for each individual by assuming that it is a β distribution with mean $\rho_{i,s,t,\tau}$, and an unknown variance ν_i(which will be the second parameter estimated in the model). Using Bayes' Rule, the poll result, along with ψ and the prior distribution, will fully characterize the posterior distribution of states for any individual. We will estimate ψ_i and ν_i jointly for each individual using generalized methods of moments. We will match five moments. The first two are simply each individual's probability of the state gubernatorial election being decided by less than 100 votes or less than 1000 votes before the treatment. The second two are each individual's probability of the state gubernatorial election being decided by less than 100 votes or less than 1000 votes after the treatment. The final moment is the change in the mean margin of victory given by the individual from before the treatment to after the treatment.[27]

7 Conclusion

Our results shed light on two important areas of research in economics — voting behavior and biases in probabilistic judgement. We find that NBLLN provides a tractable model that better captures beliefs and learning from polls than a neo-classical model. However, we find that even individual's overestimation of their likelihood of being pivotal cannot save the pivotal voting model – individuals' beliefs about their likelihood of being pivotal do nor influence their likelihood of voting.

Our results for two reasons. First because they provide important field evidence on the existence of biases in probabilistic judgement. The data allow us to structurally estimate a model of NBLLN, and

[27] Estimating parameters for each individual separately cannot allow us to address issues of focal point responses. In order to attempt to correct for this, we first need to develop a structural model of changing responses to focal points. This also requires an assumption regarding the form of the underlying distribution of ψ in the population, e.g. log-normal. We then estimate the parameters of both the model of coal points and the parameters of the distribution of ψ using the observed distribution of beliefs.

support the contention that experimentally elicited parameters can predict outcomes in similar real-world situations. Although other possible reasons could explain either the belief in close elections, or the lack of updating, our model can explain both at the same time, as well as the correlation between them. Furthermore, our model parsimoniously captures the relationship between the experimental measures of NBLLN and the observed field data.

Second, our data are important field test of the pivotal voting model. The our analysis indicates that the pivotal voting model cannot be saved by accurately modeling individuals (incorrect) beliefs. We find that even though individuals overestimate their probability of being pivotal, differences in beliefs have no effect on whether individuals vote or not. This suggests that attempts to rationalize voting must focus on alternative explanations, such as social norms and intrinsic rewards.

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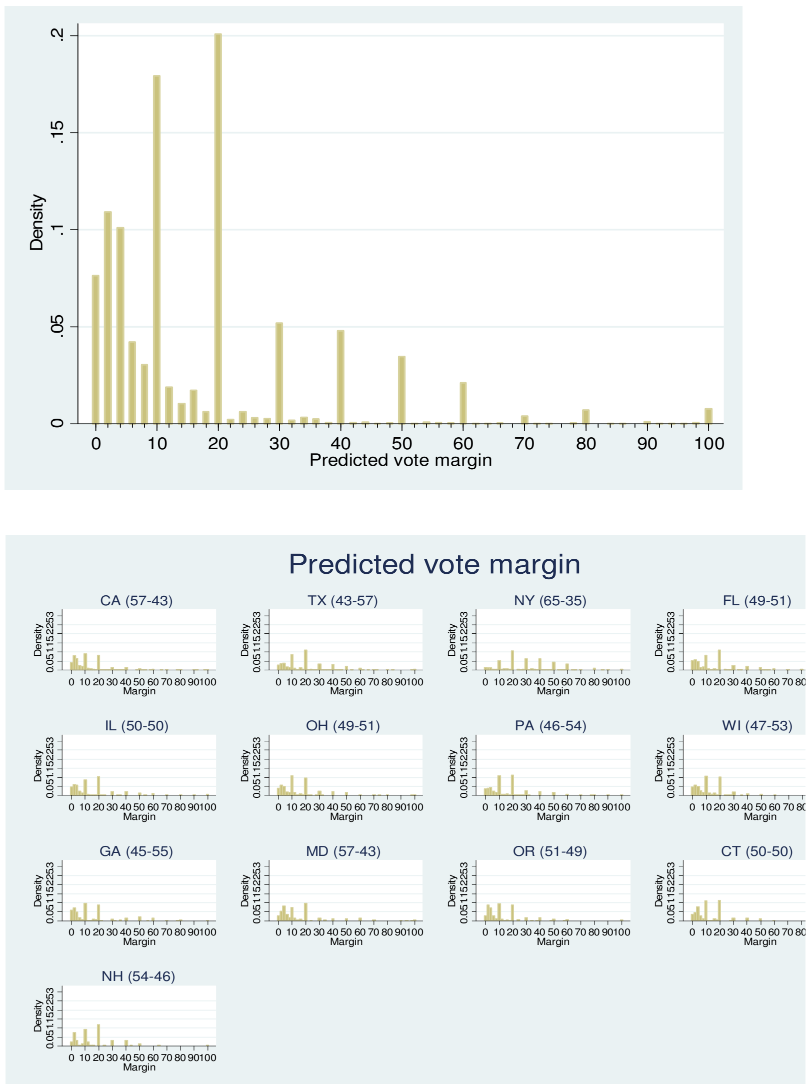
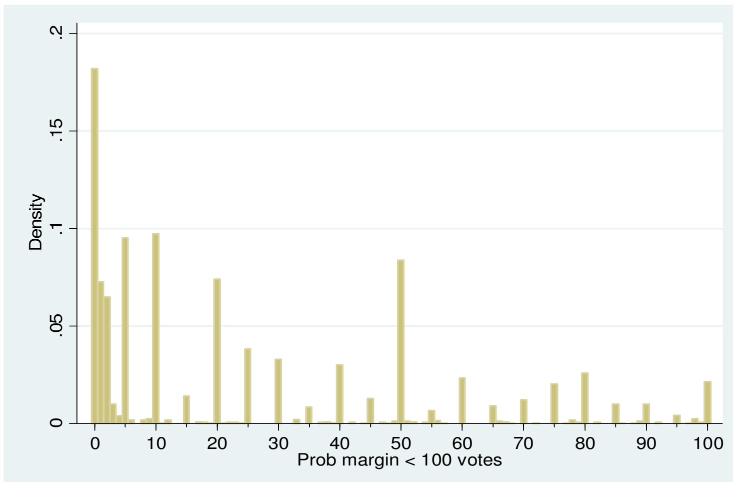
Figure 1: Distribution of the Predicted Margin of Victory



Notes: This graph plots the distribution of subjects' predicted margin of victory.

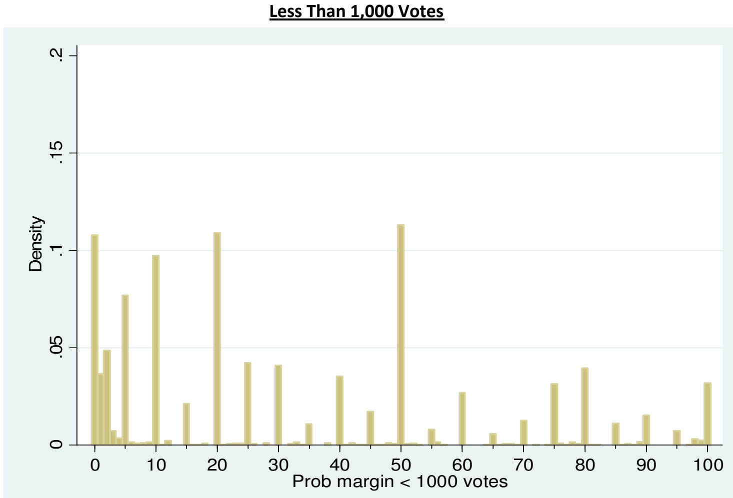
Figure 2: Subjective Probabilities that Gubernatorial Election Will be Decided by Less than 100 Votes or 1,000 Votes

Less Than 100 Votes



Median = 10, 25th Percentile = 1, 75th Percentile = 45

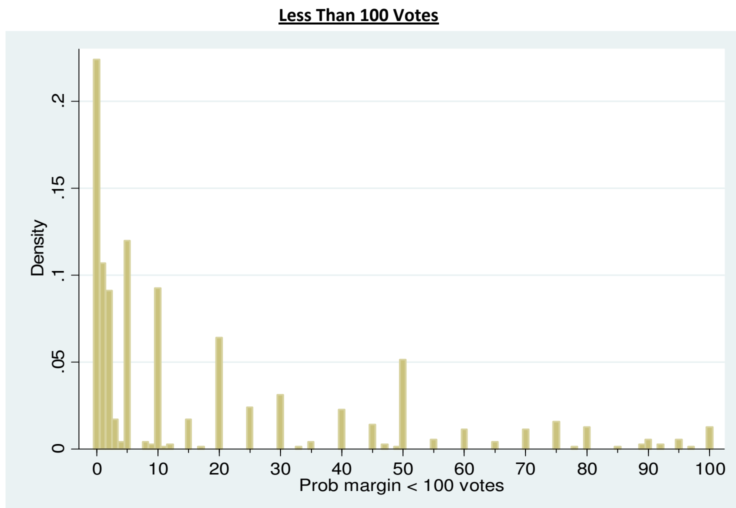
Less Than 1,000 Votes



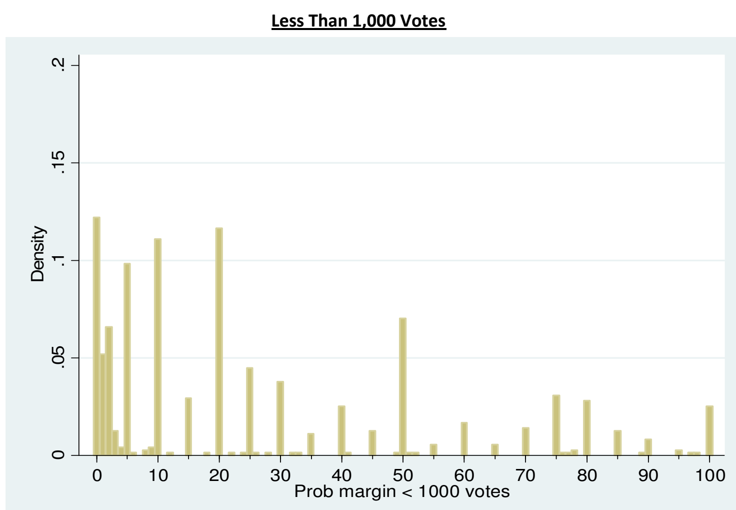
Median = 20, 25th Percentile = 5, 75th Percentile = 50

Notes: These graphs plot the distribution of answers to the question asking for the probability the election in the respondent's state would be decided by less than 100 votes or less than 1,000 votes.

Figure 3: Subjective Probabilities that Gubernatorial Election Will be Decided by Less than 100 Votes or 1,000 Votes–Voters with Master's or PhD



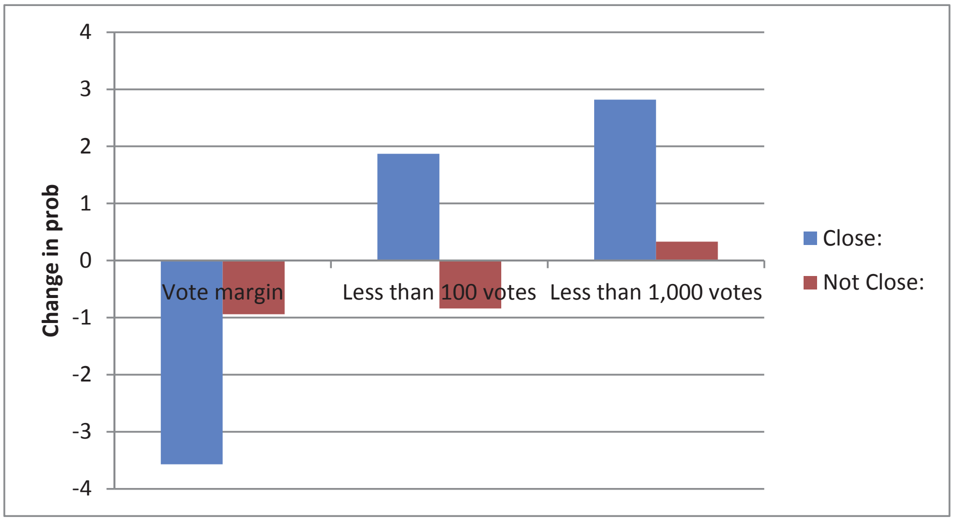
Median = 5, 25th Percentile = 1, 75th Percentile = 20



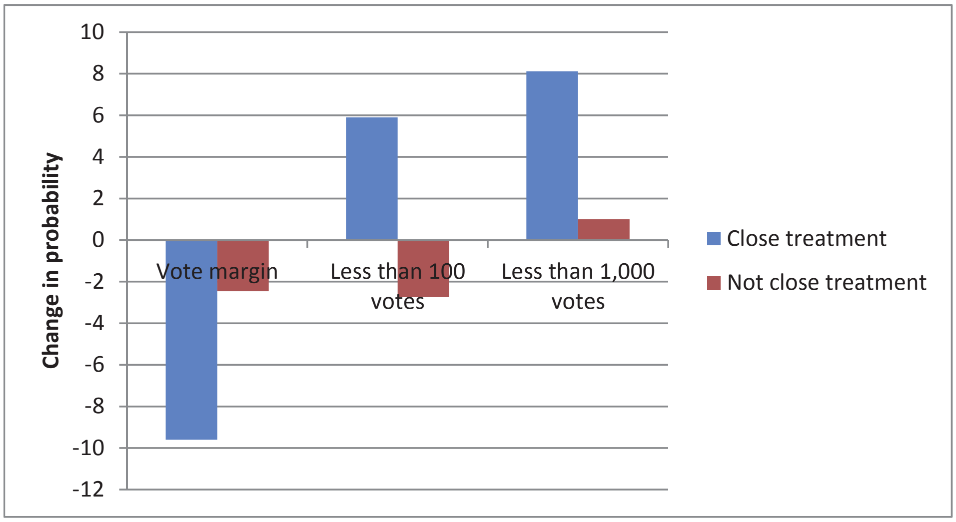
Median = 15, 25th Percentile = 3, 75th Percentile = 40

Notes: These graphs plot the distribution of answers to the question asking for the probability the election in the respondent's state would be decided by less than 100 votes or less than 1,000 votes.

Figure 4: Belief Updating in Response to Polls



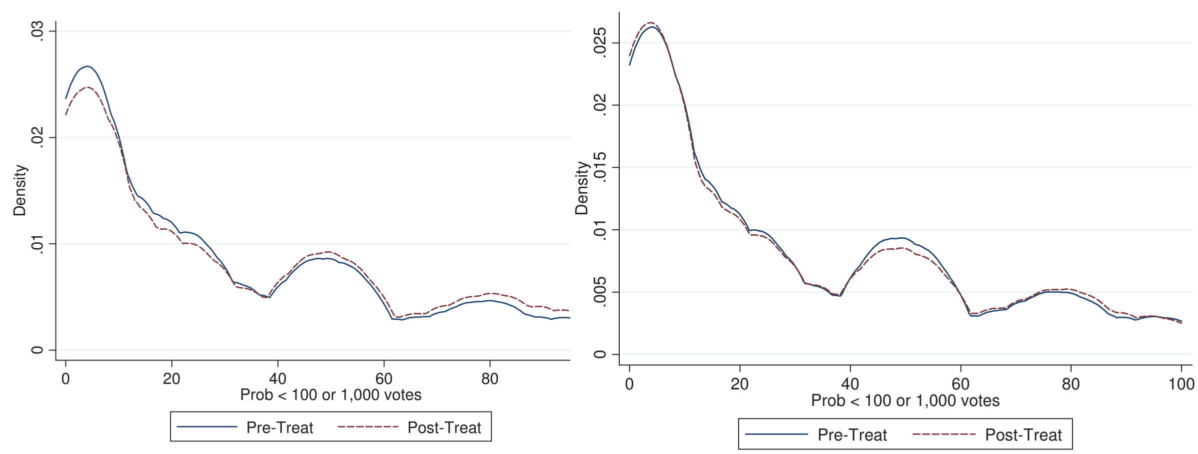
(a) Overall impact on beliefs



(b) Impact on beliefs among those who change their response

Notes: These graphs analyze the impact of the experiment on voters' beliefs.

Figure 5: Distribution of Beliefs About a Very Close Election Before and After the Close and Not Close Treatments



(a) Close Treatment

(b) Not Close Treatment

Notes: These graphs analyze the distribution of beliefs that the election will be decided by less than 100 or less than 1,000 votes. The figures are density plots with an optimal bandwidth.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: Demographics					
Male	0.39	0.49	0	1	6705
Black	0.08	0.27	0	1	6705
Hispanic	0.06	0.24	0	1	6705
Other	0.03	0.18	0	1	6705
Mixed race	0.02	0.15	0	1	6705
Age	53.33	14.2	18	93	6705
Less than high school	0.03	0.16	0	1	6705
High school degree	0.13	0.34	0	1	6705
Some college or associate degree	0.34	0.47	0	1	6705
Bachelor's degree	0.29	0.45	0	1	6705
Master's or PhD	0.21	0.41	0	1	6705
Income $25k-$50k	0.23	0.42	0	1	6705
Income $50k-$75k	0.23	0.42	0	1	6705
Income $75k-$100k	0.18	0.38	0	1	6705
Income $100k +	0.24	0.43	0	1	6705
Catholic	0.3	0.46	0	1	11452
Protestant	0.48	0.5	0	1	11452
Other Christian	0.16	0.37	0	1	11452
Jewish	0.05	0.21	0	1	11452
Panel B: Politics					
Registered Democrat	0.48	0.5	0	1	9640
Registered Republican	0.36	0.48	0	1	9640
No party affil/decline to state/indep	0.13	0.34	0	1	9640
Other party registration	0.03	0.16	0	1	9640
Identify Nancy Pelosi as Speaker	0.82	0.38	0	1	6595
Interest in politics (1-5 scale)	3.71	1.06	1	5	6684
Affiliate w/ Democrat party (1-7)	4.24	2.15	1	7	16098
Ideology (1=Extremely Conserv, 7=Extremeley Liberal)	3.88	1.52	1	7	15960
Panel C: Beliefs					
Predicted vote margin, pre-treatment	17.08	17.78	0	100	6652
Predicted vote margin, post-treatment	14.76	15.83	0	100	6650
Prob margin < 100 votes, pre-treatment	24.42	28.3	0	100	3284
Prob margin < 100 votes, post-treatment	24.95	28.97	0	100	3286
Prob margin < 1,000 votes, pre-treatment	31.69	29.7	0	100	3409
Prob margin < 1,000 votes, post-treatment	33.22	30.51	0	100	3407
Prob voting, pre-treatment	87.06	27.79	0	100	6698
Prob voting, post-treatment	87.91	27.08	0	100	6700
Prob vote Dem, pre-treatment	49.94	43.77	0	100	6705
Prob vote Republican, pre-treatment	41.5	43.08	0	100	6705
Prob vote Dem, post-treatment	50.14	43.68	0	100	6705
Prob vote Republican, post-treatment	41.72	43.03	0	100	6705
Prob vote underdog, pre-treatment	41.16	43.07	0	100	6705
Prob vote underdog, post-treatment	41.14	42.98	0	100	6705
Panel D: Voting					
Voted (self-reported)	0.84	0.36	0	1	5867
Voted (administrative)	0.66	0.47	0	1	16628
Share voted previous 5 elections (administrative)	0.59	0.39	0	1	16628

Notes: This table presents summary statistics. The 'Share voted previous 5 elections' refers to voting in the general elections of 2000, 2002, 2004, 2006, and 2008. As can be seen, our sample is more white, female, and older than the general population.

Table 2: Randomization Check

	Close (1)	Not Close (2)	t-test of (1) vs (2) (3)	Assigned Close (4)	Assigned Not Close (5)	Assigned Control (6)	t-test of (4) vs (5) (7)	t-test of (4) vs (6) (8)	t-test of (5) vs (6) (9)
Panel A: Demographics									
Male	0.39	0.39	0.91						
Black	0.08	0.08	0.87						
Hispanic	0.06	0.06	0.67						
Other	0.03	0.03	0.96						
Mixed race	0.02	0.02	0.34						
Age	53.21	53.45	0.49						
Less than high school	0.03	0.03	0.56						
High school degree	0.14	0.13	0.54						
Some college or associate degree	0.34	0.34	0.96						
Bachelor's degree	0.29	0.29	0.76						
Master's or PhD	0.21	0.21	0.91						
Income $25k-$50k	0.22	0.24	0.09						
Income $50k-$75k	0.24	0.23	0.14						
Income $75k-$100k	0.18	0.17	0.31						
Income $100k +	0.24	0.25	0.32						
Catholic	0.30	0.30	0.82	0.31	0.30	0.29	0.36	0.09	0.46
Protestant	0.48	0.48	0.80	0.48	0.48	0.47	0.73	0.71	0.48
Other Christian	0.16	0.16	0.79	0.16	0.16	0.17	0.43	0.06	0.28
Jewish	0.05	0.05	0.76	0.05	0.05	0.05	0.91	0.29	0.34
Panel B: Politics									
Registered Democrat	0.49	0.50	0.46	0.49	0.49	0.47	0.80	0.11	0.07
Registered Republican	0.36	0.35	0.77	0.35	0.35	0.37	0.56	0.04	0.15
No party affil/decline state/indep	0.13	0.12	0.58	0.14	0.12	0.13	0.14	0.41	0.50
Other party registration	0.03	0.02	0.75	0.03	0.03	0.03	0.54	0.52	0.98
Identify Nancy Pelosi as Speaker	0.82	0.83	0.23						
Interest in politics (1-5 scale)	3.73	3.70	0.31						
Affiliate w/ Democrat party (1-7)	4.23	4.24	0.87	4.26	4.25	4.20	0.80	0.14	0.23
Ideology (1-7 Scale, 7=Ext Liberal)	3.89	3.87	0.65	3.89	3.87	3.87	0.50	0.47	0.96
Panel C: Beliefs									
Predicted vote margin, pre-treat	17.05	17.10	0.91						
Prob margin < 100 votes, pre-treat	23.44	25.44	0.04						
Prob margin < 1,000 votes, pre-treat	31.93	31.46	0.65						
Prob voting, pre-treatment	87.08	87.04	0.95						
Prob vote Dem, pre-treatment	49.71	50.17	0.67						
Prob vote Republican, pre-treat	41.46	41.53	0.95						
Prob vote underdog, pre-treat	40.79	41.52	0.49						
Panel D: Voting									
Voted (self-reported)	0.84	0.85	0.62						
Voted (administrative)	0.66	0.66	0.90	0.64	0.63	0.71	0.70	0.00	0.00
Share voted previous 5 election	0.59	0.59	0.96	0.57	0.57	0.63	0.83	0.00	0.00
Number of observations	3,348	3,357		5,413	5,387	5,543			

Notes: This table presents averages across the different treatments. Columns (1) and (2) are for subjects assigned to the Close or Not Close treatments who answer the survey. (4), (5), and (6) are averages for voters assigned to the Close, Not Close, and Control treatments. The 'Share voted previous 5 elections' refers to voting in the general elections of 2000, 2002, 2004, 2006, and 2008.

Table 3: Predicting Pre-treatment Beliefs

Dep var:	Prob < 100 votes		Prob < 1,000 votes		Margin of victory		Democrat vote share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Actual vote margin in state	-0.13		-0.39		0.47		0.43	
	(0.06)**		(0.06)***		(0.03)***		(0.02)***	
Log size of electorate	-0.65		-0.43		-0.81		-1.27	
	(0.88)		(0.87)		(0.34)**		(0.23)***	
Affiliate w/ Democrat party (1-7)	0.18	0.16	0.64	0.60	-0.19	-0.11	1.64	1.51
	(0.24)	(0.24)	(0.26)**	(0.27)**	(0.11)*	(0.11)	(0.07)***	(0.07)***
Interest in politics (1-5)	-1.46	-1.50	-0.35	-0.33	-0.07	-0.01	-0.34	-0.36
	(0.54)***	(0.54)***	(0.55)	(0.55)	(0.25)	(0.25)	(0.17)**	(0.16)**
Prob in middle, coins experiment	-0.08	-0.08	-0.04	-0.04	-0.04	-0.04	-0.00	-0.00
	(0.01)***	(0.01)***	(0.02)**	(0.02)**	(0.01)***	(0.01)***	(0.00)	(0.00)
Male	-11.38	-11.36	-14.28	-14.31	-2.90	-2.89	0.30	0.22
	(0.99)***	(0.99)***	(1.06)***	(1.06)***	(0.45)***	(0.44)***	(0.30)	(0.29)
Black	14.62	14.45	3.74	3.27	4.32	4.46	4.57	5.68
	(2.46)***	(2.50)***	(2.31)	(2.36)	(1.16)***	(1.15)***	(0.75)***	(0.75)***
Hispanic	10.23	9.71	6.91	6.84	1.86	2.05	0.45	1.30
	(2.42)***	(2.45)***	(2.47)***	(2.51)***	(1.13)	(1.14)*	(0.79)	(0.78)*
Other	8.29	7.94	0.80	0.36	0.35	1.57	0.19	-0.14
	(3.16)***	(3.17)**	(2.74)	(2.71)	(1.37)	(1.35)	(0.92)	(0.92)
Mixed race	6.19	6.60	1.19	0.76	0.10	0.47	-0.15	-0.52
	(3.93)	(3.90)*	(3.96)	(3.91)	(1.42)	(1.43)	(1.17)	(1.13)
Age 25-34	4.17	4.29	-0.41	-0.24	-4.32	-4.60	2.21	1.91
	(3.96)	(3.96)	(3.78)	(3.77)	(2.49)*	(2.53)*	(1.72)	(1.69)
Age 35-44	2.32	2.43	1.88	2.18	-4.84	-5.06	2.35	2.03
	(3.72)	(3.70)	(3.60)	(3.59)	(2.43)**	(2.47)**	(1.66)	(1.63)
Age 45-54	3.22	3.26	-0.19	0.05	-5.01	-5.26	2.92	2.57
	(3.67)	(3.66)	(3.53)	(3.50)	(2.42)**	(2.46)**	(1.65)*	(1.62)
Age 55-64	2.27	2.32	0.93	1.35	-6.29	-6.71	2.61	2.02
	(3.70)	(3.69)	(3.48)	(3.46)	(2.41)***	(2.45)***	(1.64)	(1.61)
Age 65-74	1.19	1.02	-0.25	-0.09	-7.88	-8.05	3.13	2.33
	(3.76)	(3.74)	(3.57)	(3.55)	(2.42)***	(2.47)***	(1.64)*	(1.61)
Age 75 or more	8.08	7.96	2.43	2.90	-9.12	-9.43	4.15	2.97
	(4.26)*	(4.25)*	(3.97)	(3.96)	(2.48)***	(2.52)***	(1.67)**	(1.64)*
Less than high school	8.35	8.42	-4.99	-5.00	-1.18	-1.10	0.81	0.59
	(4.12)**	(4.13)**	(4.05)	(4.07)	(2.34)	(2.33)	(1.56)	(1.55)
Some college or associate degree	-1.82	-2.04	-3.79	-4.13	-2.98	-2.34	-0.58	-0.72
	(1.87)	(1.87)	(1.85)**	(1.85)**	(0.87)***	(0.87)***	(0.58)	(0.57)
Bachelor's degree	-7.11	-7.33	-6.99	-7.36	-5.45	-4.80	0.63	0.56
	(1.89)***	(1.90)***	(1.90)***	(1.89)***	(0.85)***	(0.85)***	(0.57)	(0.56)
Master's or PhD	-9.13	-9.22	-9.04	-9.41	-6.35	-5.94	1.18	0.93
	(1.98)***	(1.98)***	(2.00)***	(2.00)***	(0.88)***	(0.87)***	(0.58)**	(0.57)
Income $25k-$50k	0.95	1.10	0.53	0.23	-0.70	-0.83	-0.31	-0.07
	(2.01)	(2.02)	(1.96)	(1.95)	(0.93)	(0.92)	(0.63)	(0.62)
Income $50k-$75k	-2.16	-2.19	-1.27	-1.63	-1.30	-1.32	-0.56	-0.33
	(1.93)	(1.93)	(1.96)	(1.97)	(0.91)	(0.90)	(0.62)	(0.61)
Income $75k-$100k	-2.62	-2.44	-2.87	-3.45	-2.09	-2.15	-0.58	-0.46
	(2.00)	(2.01)	(2.06)	(2.06)*	(0.91)**	(0.89)**	(0.62)	(0.60)
Income $100k +	-5.17	-5.20	-8.62	-9.38	-1.40	-1.10	-0.37	-0.44
	(1.92)***	(1.92)***	(1.93)***	(1.93)***	(0.91)	(0.90)	(0.62)	(0.60)
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2717	2717	2773	2773	5462	5462	5479	5479
R-squared	0.16	0.16	0.13	0.14	0.11	0.14	0.21	0.27

Notes: This table presents OLS regressions of voters' pre-treatment beliefs on various covariates. It covers voters' perception the election is decided by less than 100 or 1,000 votes, as well as voters' predictions of the vote margin and vote share for the Democrat. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Changes in Beliefs and Voting Intentions After the Treatment

	N	Decrease	Same	Increase	N	Decrease	Same	Increase
	Not Close Treatment				Close Treatment			
Predicted margin of victory	3311	19.0%	61.8%	19.2%	3301	30.1%	62.8%	7.1%
Prob margin < 100 votes	1601	18.2%	69.3%	12.6%	1681	11.3%	68.2%	20.5%
Prob margin < 1000 votes	1749	18.4%	67.3%	14.3%	1657	10.4%	65.3%	24.3%
Intended prob of voting	3350	3.4%	88.3%	8.3%	3347	3.7%	88.0%	8.4%
Intended prob of voting for underdog	3357	6.1%	87.7%	6.3%	3348	5.7%	88.2%	6.1%
	Treatment That's Less Favorable for Democrat				Treatment That's More Favorable for Democrat			
Predicted Dem vote share	3,364	25.6%	61.3%	13.1%	3,301	14.3%	59.0%	26.7%
Pred Dem vote share, affil w/ Dem party	1,798	29.5%	59.0%	11.5%	1,765	17.6%	56.7%	25.8%
Pred Dem vote share, don't affiliate w/ Dem party	1,552	20.8%	64.2%	15.0%	1,519	10.3%	61.8%	27.9%
Intended prob of voting for Democrat	3384	5.3%	88.1%	6.6%	3321	5.9%	87.3%	6.7%

Notes: This table describes how voters' perception of the vote margin, their perception the election is decided by less than 100 or 1,000 votes, their predicted probability of voting, and their intended probability of voting for the underdog candidate (the candidate behind in the polls) change under the two information treatments (close poll and not close poll). In addition, it shows how the intended probability of voting for the Democrat changes under the poll that is less favorable to the Democrat and the poll that is more favorable to the Democrat.

Table 5: The Effect of the Close Poll Treatment on Vote Margin Predictions

Panel A: Treatment Var is Discrete

Dep. var = Predicted vote margin	b_{post} (1)	b_{post} (2)	Δb (3)	b_{post} (4)	b_{post} (5)	b_{post} (6)	b_{post} (7)
Close poll treatment	-2.80***	-2.79***	-2.62***	-2.72***	-5.45***	-3.83***	-4.66***
	(0.39)	(0.36)	(0.34)	(0.36)	(1.44)	(1.00)	(0.78)
Close poll*Interest in politics (1-5 scale)					0.73**		
					(0.36)		
Close poll*Identify Nancy Pelosi as Speaker						1.35	
						(1.07)	
Close poll*Share voted previous 5 elections							2.98***
							(1.01)
Interest in politics (1-5 scale)				-0.03	-0.38	-0.03	-0.01
				(0.21)	(0.27)	(0.21)	(0.21)
Identify Nancy Pelosi as Speaker				-1.59***	-1.60***	-2.27***	-1.60***
				(0.54)	(0.54)	(0.78)	(0.54)
Share voted previous 5 elections (admin)				-1.16**	-1.15**	-1.17**	-2.66***
				(0.56)	(0.56)	(0.56)	(0.77)
State FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Demog Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6650	6650	6612	6529	6529	6529	6529
R-squared	0.01	0.10	0.02	0.14	0.14	0.14	0.14

Panel B: Treatment Var is Continuous

Dep. var = Predicted vote margin	b_{post} (1)	b_{post} (2)	Δb (3)	b_{post} (4)	b_{post} (5)	b_{post} (6)	b_{post} (7)
Margin in viewed poll	0.42***	0.22***	0.21***	0.22***	0.35***	0.24***	0.30***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.09)	(0.06)	(0.05)
Viewed margin*Interest in politics (1-5 scale)					-0.03		
					(0.02)		
Viewed margin*Identify Nancy Pelosi as Speaker						-0.02	
						(0.06)	
Viewed margin*Share voted previous 5 elections							-0.13*
							(0.06)
Interest in politics (1-5 scale)				-0.02	0.30	-0.02	-0.01
				(0.21)	(0.28)	(0.21)	(0.21)
Identify Nancy Pelosi as Speaker				-1.53***	-1.53***	-1.33*	-1.53***
				(0.54)	(0.54)	(0.77)	(0.54)
Share voted previous 5 elections (administrative)				-1.13**	-1.13**	-1.14**	0.05
				(0.56)	(0.56)	(0.56)	(0.77)
State FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6650	6650	6612	6529	6529	6529	6529
R-squared	0.06	0.14	0.03	0.15	0.15	0.15	0.15

Notes: Robust standard errors in parentheses. Demographic controls include gender, race, 10-year age bins, education dummies, and $25k income bins. When the treatment variable is used in discrete form, it is a dummy for getting the close poll (versus getting the not close poll). When the treatment variable is continuous, it is equal to the vote margin in the viewed poll (e.g. if the voter was shown a 55-45 poll, the margin in viewed poll is equal to 10). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: The Effect of the Close Poll Treatment on the Perceived Likelihood of the Election Being Decided by Less than 100 or Less than 1,000 Votes

Panel A: Treatment Var is Discrete

	Prob < 100 votes			Prob < 1,000 votes			< 100 or 1,000 votes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Close poll treatment	0.80	2.47	2.54	2.93	2.55	2.33	1.67	2.47	2.43
	(1.01)	(0.53)***	(0.53)***	(1.04)***	(0.53)***	(0.52)***	(0.73)**	(0.38)***	(0.37)***
Prob <100 votes, pre-treat		0.87	0.85						
		(0.01)***	(0.01)***						
Prob <1,000 votes, pre-treat					0.88	0.86			
					(0.01)***	(0.01)***			
Prob <100 or 1,000 votes, pre-treat								0.88	0.86
								(0.01)***	(0.01)***
Demog Controls	No	No	Yes	No	No	Yes	No	No	Yes
State FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	3286	3282	3282	3407	3406	3406	6693	6688	6688
R-squared	0.00	0.73	0.73	0.00	0.74	0.75	0.00	0.74	0.75

Panel B: Treatment Var is Continuous

	Prob < 100 votes			Prob < 1,000 votes			< 100 or 1,000 votes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Margin in viewed poll	-0.10	-0.13	-0.14	-0.39	-0.19	-0.14	-0.24	-0.16	-0.14
	(0.06)*	(0.03)***	(0.04)***	(0.05)***	(0.03)***	(0.04)***	(0.04)***	(0.02)***	(0.02)***
Prob <100 votes, pre-treat		0.87	0.85						
		(0.01)***	(0.01)***						
Prob <1,000 votes, pre-treat					0.88	0.86			
					(0.01)***	(0.01)***			
Prob <100 or 1,000 votes, pre-treat								0.88	0.86
								(0.01)***	(0.01)***
Demog Controls	No	No	Yes	No	No	Yes	No	No	Yes
State FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	3286	3282	3282	3407	3406	3406	6693	6688	6688
R-squared	0.00	0.72	0.73	0.01	0.75	0.75	0.01	0.74	0.75

Notes: The dependent variable is a voter's post-treatment belief that the election will be decided by less than 100 votes or less than 1,000 votes. Voters were either asked about 100 votes or about 1,000 votes. The data is pooled in columns 7-9. Robust standard errors in parentheses. Demographic controls include gender, race, 10-year age bins, education dummies, and $25k income bins. When the treatment variable is used in discrete form, it is a dummy for getting the close poll (versus getting the not close poll). When the treatment variable is continuous, it is equal to the vote margin in the viewed poll (e.g. if the voter was shown a 55-45 poll, the margin in viewed poll is equal to 10). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Correlation Between Beliefs About the Closeness of the Election and Voter Turnout, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pred vote margin, post-treat	-0.056	-0.012						
	(0.039)	(0.051)						
Pred vote margin, pre-treat		-0.068						
		(0.046)						
Pr(Marg <100 votes), post			-0.036	0.064				
			(0.029)	(0.052)				
Pr(Marg <100 votes), pre				-0.123				
				(0.054)**				
Pr(Marg <1,000 votes), post					0.021	0.017		
					(0.027)	(0.051)		
Pr(Marg <1,000 votes), pre						0.006		
						(0.052)		
<100 or 1,000 votes, post							-0.008	0.037
							(0.020)	(0.036)
<100 or 1,000 votes, pre								-0.054
								(0.038)
Male	2.782	2.691	0.746	0.504	4.366	4.369	2.607	2.503
	(1.107)**	(1.111)**	(1.624)	(1.627)	(1.638)***	(1.641)***	(1.147)**	(1.149)**
Black	0.083	0.317	1.157	1.731	-1.073	-1.089	-0.078	0.098
	(2.229)	(2.254)	(3.134)	(3.154)	(3.112)	(3.113)	(2.210)	(2.215)
Hispanic	-3.249	-3.087	-1.165	-0.502	-5.721	-5.727	-3.515	-3.324
	(2.449)	(2.448)	(3.753)	(3.767)	(3.194)*	(3.196)*	(2.438)	(2.443)
Other	-4.026	-4.073	1.793	1.943	-8.957	-8.955	-3.992	-3.977
	(3.123)	(3.121)	(4.296)	(4.298)	(4.406)**	(4.407)**	(3.105)	(3.106)
Mixed race	4.509	3.858	11.282	11.668	-1.047	-1.069	4.620	4.832
	(3.601)	(3.631)	(5.044)**	(5.019)**	(5.072)	(5.083)	(3.611)	(3.621)
Age 25-34	2.622	2.908	6.263	6.934	0.732	0.724	3.090	3.354
	(4.463)	(4.487)	(6.540)	(6.561)	(5.990)	(5.993)	(4.442)	(4.445)
Age 35-44	22.838	22.803	23.928	24.187	22.864	22.849	23.428	23.538
	(4.216)***	(4.239)***	(6.207)***	(6.218)***	(5.641)***	(5.646)***	(4.193)***	(4.195)***
Age 45-54	29.460	29.437	30.508	31.025	29.142	29.127	29.821	30.021
	(4.116)***	(4.139)***	(6.038)***	(6.047)***	(5.526)***	(5.531)***	(4.093)***	(4.094)***
Age 55-64	34.154	34.239	34.939	35.326	34.770	34.736	34.765	34.975
	(4.095)***	(4.118)***	(6.053)***	(6.063)***	(5.458)***	(5.464)***	(4.074)***	(4.075)***
Age 65-74	42.136	41.956	43.978	44.431	42.091	42.069	42.942	43.156
	(4.127)***	(4.151)***	(6.065)***	(6.075)***	(5.527)***	(5.537)***	(4.108)***	(4.111)***
Age 75 or more	44.959	44.733	46.896	47.696	44.784	44.766	45.673	45.939
	(4.352)***	(4.381)***	(6.398)***	(6.411)***	(5.855)***	(5.862)***	(4.335)***	(4.340)***
Less than high school	-9.762	-10.629	-13.542	-13.045	-6.704	-6.712	-10.086	-10.007
	(4.307)**	(4.360)**	(6.184)**	(6.229)**	(5.991)	(5.992)	(4.276)**	(4.283)**
Some college or assoc deg	2.219	2.506	2.546	2.455	2.996	2.991	2.628	2.539
	(1.876)	(1.881)	(2.645)	(2.638)	(2.655)	(2.656)	(1.868)	(1.869)
Bachelor's degree	8.599	8.579	11.204	10.872	7.370	7.375	9.151	9.010
	(1.935)***	(1.939)***	(2.752)***	(2.746)***	(2.721)***	(2.722)***	(1.930)***	(1.931)***
Master's or PhD	10.902	10.780	12.675	12.539	9.761	9.772	11.153	11.047
	(2.025)***	(2.030)***	(2.883)***	(2.875)***	(2.868)***	(2.874)***	(2.023)***	(2.023)***
Income $25k-$50k	9.414	9.578	8.638	8.561	10.273	10.271	9.647	9.640
	(2.105)***	(2.107)***	(2.976)***	(2.976)***	(2.966)***	(2.967)***	(2.095)***	(2.095)***
Income $50k-$75k	11.952	11.810	12.170	12.177	12.023	12.003	12.233	12.303
	(2.107)***	(2.108)***	(2.934)***	(2.931)***	(3.002)***	(3.004)***	(2.094)***	(2.093)***
Income $75k-$100k	12.925	12.668	14.050	13.948	11.469	11.466	12.946	12.937
	(2.222)***	(2.223)***	(3.074)***	(3.069)***	(3.201)***	(3.201)***	(2.217)***	(2.215)***
Income $100k +	14.753	14.690	14.737	14.776	15.234	15.238	15.048	15.097
	(2.154)***	(2.155)***	(3.027)***	(3.023)***	(3.045)***	(3.047)***	(2.148)***	(2.147)***
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6125	6090	3047	3043	3119	3118	6166	6161
R-squared	0.14	0.14	0.15	0.15	0.14	0.14	0.14	0.14

Notes: This table reports OLS regressions where the dependent variable is turnout (0-1) from administrative voting records. Coefficients are multiplied by 100 for ease of readability. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Beliefs About the Closeness of the Election and Voter Turnout, IV Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred vote margin, post-treat	0.13	0.13	0.05									
	(0.39)	(0.40)	(0.39)									
Pred vote margin, pre-treat		-0.30	-0.12									
		(0.22)	(0.21)									
Pr(Marg <100 votes), post				-1.30	-0.51	-0.49						
				(2.26)	(0.62)	(0.59)						
Pr(Marg <100 votes), pre					0.31	0.36						
					(0.54)	(0.50)						
Pr(Marg <1,000 votes), post							0.03	0.03	0.35			
							(0.54)	(0.61)	(0.63)			
Pr(Marg <1,000 votes), pre								-0.06	-0.26			
								(0.54)	(0.54)			
<100 or 1,000 votes, post										-0.28	-0.20	-0.08
										(0.66)	(0.44)	(0.43)
<100 or 1,000 votes, pre											0.10	0.06
											(0.39)	(0.37)
F-stat on excl instrument	56.33	86.85	86.65	0.726	22.76	23.25	7.384	21.97	19.86	5.199	43.42	42.89
Demog Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,650	6,612	6,612	3,286	3,282	3,282	3,407	3,406	3,406	6,693	6,688	6,688
R-squared	0.02	0.03	0.12	-0.54	0.01	0.09	0.02	0.02	0.11	0.01	0.02	0.12

Notes: The dependent variable is turnout (0-1) from administrative voting records. In all specifications, post-treatment beliefs are instrumented with a dummy variable for receiving the close poll treatment. Coefficients are multiplied by 100 for ease of readability. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Beliefs About the Closeness of the Election and Intended Probability of Voting, IV Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred vote margin, post-treat	0.13	0.13	0.05									
	(0.39)	(0.40)	(0.39)									
Pred vote margin, pre-treat		-0.30	-0.12									
		(0.22)	(0.21)									
Pr(Marg <100 votes), post				-1.30	-0.51	-0.49						
				(2.26)	(0.62)	(0.59)						
Pr(Marg <100 votes), pre					0.31	0.36						
					(0.54)	(0.50)						
Pr(Marg <1,000 votes), post							0.03	0.03	0.35			
							(0.54)	(0.61)	(0.63)			
Pr(Marg <1,000 votes), pre								-0.06	-0.26			
								(0.54)	(0.54)			
<100 or 1,000 votes, post										-0.28	-0.20	-0.08
										(0.66)	(0.44)	(0.43)
<100 or 1,000 votes, pre											0.10	0.06
											(0.39)	(0.37)
F-stat on excl instrument	55.85	86.28	86.12	0.751	23.03	23.49	7.349	21.92	19.81	5.219	43.61	43.07
Demog Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,645	6,607	6,607	3,285	3,281	3,281	3,406	3,405	3,405	6,691	6,686	6,686
R-squared	0.01	0.02	0.13	-2.13	-0.04	0.06	-0.07	-0.02	0.06	0.00	0.02	0.13

Notes: The dependent variable is the post-treatment intended probability of voting (ranging from 0%-100%). In all specifications, post-treatment beliefs are instrumented with a dummy variable for receiving the close poll treatment. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10: Beliefs About the Closeness of the Election and Information Acquisition, IV Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred vote margin, post-treat	0.60	0.55	0.55									
	(0.44)	(0.42)	(0.42)									
Pred vote margin, pre-treat		-0.25	-0.26									
		(0.23)	(0.23)									
Pr(Marg <100 votes), post				-1.16	-0.44	-0.37						
				(1.90)	(0.59)	(0.60)						
Pr(Marg <100 votes), pre					0.35	0.29						
					(0.51)	(0.51)						
Pr(Marg <1,000 votes), post							-0.70	-0.86	-0.94			
							(0.61)	(0.71)	(0.75)			
Pr(Marg <1,000 votes), pre								0.76	0.79			
								(0.63)	(0.65)			
<100 or 1,000 votes, post										-0.86	-0.63	-0.65
										(0.69)	(0.46)	(0.46)
<100 or 1,000 votes, pre											0.54	0.54
											(0.40)	(0.40)
F-stat on excl instrument	47.52	85.70	86.16	0.98	25.77	24.89	7.34	18.69	17.28	6.24	43.53	42.64
Demog Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5790	5758	5758	2874	2871	2871	2957	2956	2956	5831	5827	5827

Notes: The dependent variable is whether an agent started to pay less attention (coded as -1), more attention (coded as +1), or the same amount of attention (coded as 0) after being exposed to a poll, as reported in the post-election survey. In all specifications, post-treatment beliefs are instrumented with a dummy variable for receiving the close poll treatment. Coefficients are multiplied by 100 for ease of readability. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: Testing for the Bandwagon Effect: The Effect of Beliefs About Democrat Likely Vote Share on Voting for the Democratic Candidate, IV Results

	(1)	(2)	(3)	(4)
Predicted Dem share, post-treatment	1.12	0.43	0.50	0.44
	(0.16)***	(0.80)	(0.72)	(0.71)
Predicted Dem share, pre-treatment			1.55	1.41
			(0.44)***	(0.42)***
Constant	-2.74	39.71	-46.83	-29.29
	(8.18)	(44.12)	(17.52)***	(20.05)
F-stat on excl instrument (Dem vote share in shown poll)	798.30	35.92	66.26	65.81
Demong Controls	No	No	No	Yes
State FE	No	Yes	Yes	Yes
Observations	4211	4211	4201	4201

Notes: The dependent variable is whether a voter voted for the Democratic candidate and is self-reported. In all specifications, the voters' beliefs about the likely Democratic vote share are instrumented with the Democratic vote share in the poll they were shown. Coefficients are multiplied by 100 for ease of readability. Demographic controls include gender, race, 10-year age bins, education dummies, and $25k income bins. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

APPENDIX: FOR ONLINE PUBLICATION ONLY

A Proofs

Proposition 1: *An equilibrium exists. Furthermore, in any equilibrium, both A and B voters participate at strictly positive rates less than one.*

Proof: A fixed point consists of a self-mapping of (p_A, p_B, π_A, π_B). Since best responses are continuous and bounded from above and below, it then immediately follows (from Brouwer) that a fixed point exists. Establishing that A voters participate at strictly positive rates amounts to showing that, in any equilibrium, either $p_A > 0$ or $\pi_A > 0$ or both. To see this, suppose to the contrary that $p_A = \pi_A = 0$. In that case, any given voter preferring A faces a strictly positive probability that she is the only voter. Therefore, $\Pr[Piv_A|A] > 0$ and $\mathcal{P}[Piv_A|A] > 0$. But this implies that either p_A or $\pi_A > 0$, which is a contradiction. A similar argument holds for voters favoring B.To establish that full participation (i.e. $p_A, \pi_A < 1$) does not arise in equilibrium, notice that, since $v_A < 1$, then $v_A \Pr[Piv_A|A] < 1$ (resp. $v_A \mathcal{P}[Piv_A|A] < 1$) and hence p_A (resp. π_A)< 1. □

Lemma 1: *Suppose $\sigma_A < \sigma_B$, then $\mathcal{P}[Piv_A] > \mathcal{P}[Piv_B]$.*

Proof: □

Proposition 2: *For all γ, all voting equilibria in large elections are utilitarian. That is, the candidate favored by a social planner placing equal weight on all voters wins with probability going to one as the size of the electorate grows unbounded.*

Proof: The proof is by contradiction. Suppose that the "wrong" candidate, say A, enjoys higher vote share in the limit. Assume that Remark **??** holds, so only NBLLNs participate in the limit. In that case, the equilibrium participation conditions are

$$\begin{aligned} \pi_A &= v_A \mathcal{P}[Piv_A|A] \\ \pi_B &= v_B \mathcal{P}[Piv_B|B] \end{aligned}$$

Multiplying this by the fraction of each type, θ, to obtain expected vote shares

$$\frac{\theta \pi_A}{(1-\theta)\pi_B} = \frac{\sigma_A}{\sigma_B} = \frac{\theta v_A}{(1-\theta) v_B} \frac{\mathcal{P}[Piv_A|A]}{\mathcal{P}[Piv_B|B]}$$

Thus, $\frac{\sigma_A}{\sigma_B} > 1$ since the wrong candidate enjoys the higher vote share while $\frac{\theta v_A}{(1-\theta)v_B} < 1$ since B is the utilitarian choice. Now, by Lemma A, we know that $\frac{\mathcal{P}[Piv_A|A]}{\mathcal{P}[Piv_B|B]} < 1$, which contradicts the equilibrium equality. To establish that the correct candidate is chosen with probability approaching 1, notice that, in a Poisson setting, the limiting variation in the number of voters is $\sqrt{n}/n$, which goes to zero in the limit. Therefore, the winning candidate is one who enjoys the higher expected vote share.□

Proposition 3: *Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that welfare is ε away from 1/2. Then,*

1. *For all $\zeta \in (0,1)$, there exists an n' such that, for all $n > n'$, In every subsequence, Bayesians estimate the chance of an 2ε close election as being less than ζ.*

2. *There exists $\xi^* \in (0,1)$, such that, for all $n > n''$, NBLLNs estimate the chance of a 2ε close election as being greater than ξ^* in every convergent subsequence.*

Proof: Part 1. First, notice that, if no convergent subsequence exists, the result is satisfied trivially since the chance of a 2ε close election goes to zero. If a convergent subsequence exists, then the chance of a 2ε close election is maximized for the sequence converging to $\frac{\sigma^*_{A,n}}{\sigma^*_{B,n}}$. Specifically, the worst-case bound occurs when $\frac{\sigma^*_{A,n}}{\sigma^*_{B,n}} \to 1+\varepsilon$ (resp. $1-\varepsilon$); therefore, it suffices to show that the chance of a 2ε close election is greater than or equal to 2ε under the vote share ratio evaluated at this point. Suppose that k voters select A and l voters select B. Then an election is 2ε close iff

$$\left| \frac{k}{k+l} - \frac{l}{k+l} \right| \leq 2\varepsilon$$

or equivalently, for a given k, then

$$\begin{aligned} k - l &\leq 2\varepsilon (k+l) \\ k &> l \geq \frac{1-2\varepsilon}{1+2\varepsilon} k \end{aligned}$$

or

$$\begin{aligned} -\frac{k}{k+l}+\frac{l}{k+l} &\leq 2\varepsilon \\ l-k &\leq 2\varepsilon\left(k+l\right) \\ k &< l\leq\frac{1+2\varepsilon}{1-2\varepsilon}k \end{aligned}$$

and hence, the probability of a 2ε close election is simply

$$\Pr\left(2\varepsilon\right)=\sum_k\sum_l\Pr\left[\left(k,l\right)|\left|\frac{k}{k+l}-\frac{l}{k+l}\right|\leq 2\varepsilon\right]$$

or, equivalently

$$\begin{aligned} \Pr\left(2\varepsilon\right) &= \sum_{k=0}^{\infty}\sum_{l=\frac{1-2\varepsilon}{1+2\varepsilon}k}^{k}\Pr\left[k\right]\Pr\left[l\right]+\sum_{k=0}^{\infty}\sum_{l=k}^{\frac{1+2\varepsilon}{1-2\varepsilon}k}\Pr\left[k\right]\Pr\left[l\right] \\ &= e^{-n\left(\sigma_{A,n}+\sigma_{B,n}\right)}\left(\sum_{k=0}^{\infty}\sum_{l=\frac{1-2\varepsilon}{1+2\varepsilon}k}^{k}\frac{\left(n\lambda\sigma_A\right)^k}{k!}\frac{\left(n\left(1-\lambda\right)\sigma_B\right)^l}{l!}++\sum_{k=0}^{\infty}\sum_{l=k}^{\frac{1+2\varepsilon}{1-2\varepsilon}k}\frac{\left(n\lambda\sigma_A\right)^k}{k!}\frac{\left(n\left(1-\lambda\right)\sigma_B\right)^l}{l!}\right) \\ &= e^{-n\left(\sigma_{A,n}+\sigma_{B,n}\right)}\left(I_0\left(2n\sqrt{\sigma_A\sigma_B}\right)+I_1\left(2n\sqrt{\sigma_A\sigma_B}\right)\left(\sum_{j=-\frac{1-2\varepsilon}{1+2\varepsilon}k}^{\frac{1+2\varepsilon}{1-2\varepsilon}k}\left(\sqrt{\frac{\sigma_A}{\sigma_B}}\right)^j\right)\right) \end{aligned}$$

where I_k is the Bessel I function of type k. □

Corollary 1: *Fix a sequence of equilibria* $\left(\sigma_A,\sigma_B\right)_n$ *and* $\varepsilon>0$ *such that welfare is* ε *away from 1/2. Then there exists an* n' *such that for all* $n>n''$*, NBLLNs have a higher belief about being pivotal than Bayesians for every convergence subsequence.*

Proof: □

Proposition 4: *Fix a sequence of equilibria* $\left(\sigma_A,\sigma_B\right)_n$ *and* $\varepsilon>0$ *such that the welfare ratio is not equal to 1/2. Then for all* $\zeta\in\left(0,1\right),\iota>0$ *there exists an* n' *such that, for all* $n>n'$*, in every subsequence, Bayesians and NBLLNs estimate the chance of an* 2ε *percent close election as being less than* ζ*. However, there exists an* n'' *such that for all* $n>n''$*, NBLLNs assign a higher probability to an* ι *vote close election than Bayesians for every convergence subsequence.*

Proof: □

Proposition 5: *Fix* n *and consider two possible equilibria voting probability ratios* $\frac{\sigma_A}{\sigma_B}>\frac{\sigma_A'}{\sigma_B'}>1$ *then both Bayesians and NBLLNs believe that that the probability of either an* ϵ *or* ι *close election is higher in the equilibrium defined by* $\frac{\sigma_A}{\sigma_B}$ *than the equilibrium defined by* $\frac{\sigma_A'}{\sigma_B'}$*.*

Proof: □

Proposition 6: *Suppose* θ_1 *is the true state, and assume that polls are random samples from a population. Fix* $\theta_1,\theta_2\neq .5$*, all* $0<f_\Theta\left(\theta_1\right),f_\Theta\left(\theta_2\right)<1$*, and* $0<\zeta<1$*. Fix a sequence of equilibria* $\left(\sigma_A,\sigma_B\right)_n$*.*

1. *For all* $\tau>0$*, there exists an* N' *such that for all convergent subsequences and all* $N>N'$*, where the realization of the electorate size is greater than* N*, and the poll is of size* N*, then the probability that that a Bayesian assigns probability less than* ζ *to* θ_2 *being the true state is less than* τ*.*

2. *For all* $\zeta>0$ *and* $\tau<1$*, for all convergent subsequences and all* N*, such that the realization of the electorate size is greater than* N*, and the poll is of size* N*, then with probability* τ *the posterior probability that a NBLLN assigns to* θ_2 *being the true state is greater than* ζ *for all* N*.*

3. *For all* $\tau<1$ *there exists an* N' *such that for all convergent subsequences and all* $N>N'$*, where the realization of the electorate size is greater than* N*, and the poll is of size* N*, a NBLLN places a higher posterior on* θ_2 *being the true state compared to a Bayesian with probability greater than* τ*.*

Proof: □

Proposition 7: *Fix all parameters and an equilibrium, as well as two polls, P_1 and P_2. Assume that the proportion of individuals voting for A in P_1 is larger than in P_2. If either a NBLLN or a Bayesian sees P_1 they will place a higher posterior probability on θ_1 than if they see P_2.*

Proof: □

Proposition 8: *Suppose θ_1 is the true state, and assume that polls are random samples from a population. Fix $\theta_1, \theta_2 \neq .5$, all $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$, and $0 < \zeta < 1$. Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that welfare is ε away from 1/2.*

1. *For all $\zeta > 0$, there exists an N' such that for all convergent subsequences and all $N > N'$, where the realization of the electorate size is greater than N, and the poll is of size N, Bayesians estimate the chance of an 2ε percent close election as being less than ζ after observing a poll.*

2. *There exists $\xi^* \in (0, 1)$, such that for all convergent subsequences and all N, where the realization of the electorate size is greater than N, and the poll is of size N, NBLLNs estimate the chance of a 2ε percent close election as being greater than ξ^*.*

Proof: □ **Proposition 9:** *Fix parameters and an equilibrium. An individual with a higher probability of being pivotal will have a higher probability of voting.*

Proof: □

Proposition 10: *Suppose θ_1 is the true state, and assume that polls are random samples from a population. Fix $\theta_1, \theta_2 \neq .5$, all $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$ and an equilibria $(\sigma_A, \sigma_B)_n$. Fix a type (Bayesian or NBLLN). Then if a poll has smaller margin of victory an individual observing that poll will have a higher probability of voting.*

Proof: □

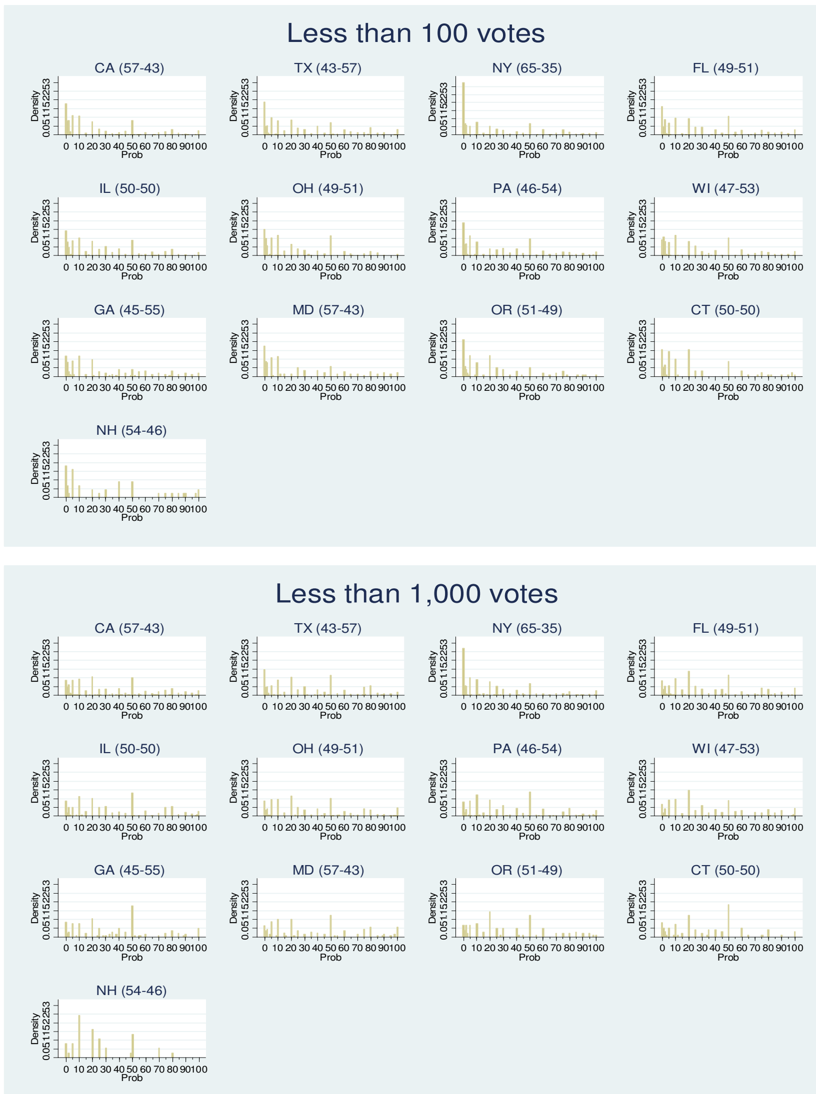
Proposition 11: *Suppose θ_1 is the true state, and assume that polls are random samples from a population. Fix $\theta_1, \theta_2 \neq .5$, all $0 < f_\Theta(\theta_1), f_\Theta(\theta_2) < 1$, and $0 < \zeta < 1$. Fix a sequence of equilibria $(\sigma_A, \sigma_B)_n$ and $\varepsilon > 0$ such that welfare is ε away from 1/2.*

1. *There exists an n' such that for all $n > n'$, NBLLNs are more likely to vote than Bayesians for every convergence subsequence.*

2. *There exists an N' such that for all convergent subsequences and all $N > N'$, where the realization of the electorate size is greater than N, and the poll is of size N NBLLNs are more likley to vote than Bayesians for every convergence subsequence after observing a random poll.*

Proof: □

Figure C1: Subjective Probabilities that Gubernatorial Election Will be Decided by Less than 100 Votes or 1,000 Votes in Different States



Notes: These graphs plot the distribution of answers to the question asking for the probability the election in the respondent's state would be decided by less than 100 votes or less than 1,000 votes in different states.

Table C1: Beliefs About the Closeness of the Election and Voter Turnout, IV Results: Sample Restricted to Voters with Middle Ideology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred vote margin, post-treat	-0.13											
	(0.58)											
Pred vote margin, change		-0.15	0.11									
		(0.73)	(0.70)									
Pr(Marg <100 votes), post				-16.4								
				(213.6)								
Pr(Marg <100 votes), ch					-0.64	-1.07						
					(1.00)	(0.94)						
Pr(Marg <1000 votes), post							0.60					
							(0.55)					
Pr(Marg <1000 votes), ch								0.91	0.93			
								(0.80)	(0.76)			
<100 or 1,000 votes, post										0.17		
										(0.81)		
<100 or 1,000 votes, ch											0.19	-0.04
											(0.62)	(0.57)
Observations	2,473	2,466	2,466	1,221	1,218	1,218	1,266	1,266	1,266	2,487	2,484	2,484
R-squared	0.04	0.03	0.13	-96.69	-0.00	0.00	-0.15	-0.06	0.07	0.01	0.03	0.13

Notes: The dependent variable is turnout (0-1) from administrative voting records. In all specifications, post-treatment beliefs are instrumented with a dummy variable for receiving the close poll treatment. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C2: Beliefs About the Closeness of the Election and Voter Turnout, IV Results: Sample Restricted to Voters with Low Interest in Government

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred vote margin, post-treat	-0.27											
	(0.54)											
Pred vote margin, change		-0.29	-0.29									
		(0.59)	(0.57)									
Pr(Marg <100 votes), post				-1.20								
				(2.66)								
Pr(Marg <100 votes), change					-0.41	-0.69						
					(0.80)	(0.75)						
Pr(Marg <1000 votes), post							1.19					
							(1.59)					
Pr(Marg <1000 votes), change								0.85	1.20			
								(0.96)	(1.10)			
<100 or 1,000 votes, post										0.27		
										(1.14)		
<100 or 1,000 votes, change											0.16	0.17
											(0.60)	(0.58)
Observations	2,593	2,573	2,573	1,284	1,281	1,281	1,327	1,326	1,326	2,611	2,607	2,607
R-squared	0.05	0.04	0.13	-0.44	0.01	0.06	-0.51	-0.06	-0.06	0.02	0.05	0.14

Notes: The dependent variable is turnout (0-1) from administrative voting records. In all specifications, post-treatment beliefs are instrumented with a dummy variable for receiving the close poll treatment. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C3: Beliefs About the Closeness of the Election and Voter Turnout, IV Results: Sample Restricted to Voters with Higher Interest in Government

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred vote margin, post-treat	0.94											
	(0.59)											
Pred vote margin, change		0.92	0.81									
		(0.57)	(0.57)									
Pr(Marg <100 votes), post				-1.79								
				(2.86)								
Pr(Marg <100 votes), change					-0.70	-0.56						
					(0.76)	(0.76)						
Pr(Marg <1000 votes), post							-0.66					
							(0.54)					
Pr(Marg <1000 votes), change								-1.07	-0.84			
								(0.85)	(0.84)			
<100 or 1,000 votes, post										-0.96		
										(0.74)		
<100 or 1,000 votes, change											-0.84	-0.71
											(0.56)	(0.56)
Observations	4,037	4,019	4,019	1,993	1,992	1,992	2,071	2,071	2,071	4,064	4,063	4,063
R-squared	-0.13	-0.04	0.02	-1.41	-0.03	0.03	-0.21	-0.15	-0.03	-0.43	-0.07	-0.00

Notes: The dependent variable is turnout (0-1) from administrative voting records. In all specifications, post-treatment beliefs are instrumented with a dummy variable for receiving the close poll treatment. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C4: Beliefs About the Closeness of the Election and Voter Turnout, IV Results: Sample Restricted to Voters who Don't Always Vote

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred vote margin, post-treat	-0.01											
	(0.47)											
Pred vote margin, change		-0.02	-0.04									
		(0.54)	(0.54)									
Pr(Marg <100 votes), post				10.47								
				(99.53)								
Pr(Marg <100 votes), change					-0.49	-0.46						
					(0.79)	(0.73)						
Pr(Marg <1000 votes), post							0.56					
							(1.01)					
Pr(Marg <1000 votes), change								0.43	0.55			
								(0.75)	(0.75)			
<100 or 1,000 votes, post										-0.11		
										(1.40)		
<100 or 1,000 votes, change											-0.02	0.02
											(0.54)	(0.52)
Observations	4,086	4,061	4,061	1,991	1,987	1,987	2,120	2,119	2,119	4,111	4,106	4,106
R-squared	0.04	0.04	0.09	-39.71	0.01	0.07	-0.10	0.00	0.05	0.04	0.04	0.09

Notes: The dependent variable is turnout (0-1) from administrative voting records. In all specifications, post-treatment beliefs are instrumented with a dummy variable for receiving the close poll treatment. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C5: The Effect of the Close Poll Treatment on Predicted Democratic Vote Share

	OLS		Constrained Regression (Regression Coefficients Sum to 1)				
Sample restriction:			Overall	Low interest in govt	Hi interest in govt	Don't usually vote	Usually vote
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pred Dem share, pre-treatment	0.60	0.59	0.61	0.56	0.65	0.59	0.63
	(0.02)***	(0.02)***	(0.02)***	(0.03)***	(0.02)***	(0.02)***	(0.02)***
Dem vote share in viewed poll	0.35	0.26	0.39	0.44	0.35	0.41	0.37
	(0.02)***	(0.03)***	(0.02)***	(0.03)***	(0.02)***	(0.02)***	(0.02)***
Constant	2.78	8.12					
	(0.85)***	(1.48)***					
State FE	No	Yes	No	No	No	No	No
Observations	6665	6665	6665	2602	4042	3398	3267
R-squared	0.57	0.57					

Notes: The dependent variable is the post-treatment predicted Democratic vote share. Robust standard errors in parentheses. In the constrained regression, the regression coefficients on the pre-treatment Democratic vote share and on the Democratic vote share in the viewed poll are required to sum to 1. "Don't usually vote" is people voting less than 80% of the time in the past 5 general elections. "Usually vote" is people voting 80% of the time or more in the past 5 general elections. * significant at 10%; ** significant at 5%; *** significant at 1%.

We will now ask you questions about the upcoming November election for the governor of Oregon. The elections will be held on Tuesday, November 2nd, 2010.

As of today, have you already voted in the November elections, for example, by absentee ballot or early voting?

Select one answer only

- Yes
- No

Next

How interested are you in information about what's going on in government and politics? Extremely interested, very interested, moderately interested, slightly interested, or not interested at all?

Select one answer only

- ○ Extremely interested
- ○ Very interested
- ○ Moderately interested
- ○ Slightly interested
- ○ Not interested at all

Next

How often would you say you vote? Seldom, part of the time, nearly always, or always?

Select one answer only

- Seldom
- Part of the time
- Nearly always
- Always

Next

What job or political office is held by Nancy Pelosi?

Select one answer only

- U.S. Secretary of State
- U.S. Secretary of Labor
- U.S. Secretary of Homeland Security
- Speaker of the U.S. House of Representatives
- Majority Leader of the U.S. Senate

Next

DOV:SHOWFIRST

Select one answer only

- DEMOCRAT
- REPUBLICAN

Next

In the election for governor, of the people voting for either the Democatic or Republican candidates, what share do you predict will vote for the Democratic candidate and what share do you predict will vote for the Republican candidate?

Type in the answer into each cell in the grid

	%
John Kitzhaber (Democrat)	
Chris Dudley (Republican)	
Total	0

Please make sure these numbers add up to 100%.

Next

DOV: VERSION

Select one answer only

- Version 2
- Version 1

Next

Many of the next questions ask you to think about the **percent chance** that something will happen in the future.

The **percent chance** can be thought of as the number of chances out of 100. You can use any number between 0 and 100 (including 0 and 100).

For example, numbers like:
1 and 2 percent may be "almost no chance",
20 percent or so may mean "not much chance",
a 45 or 55 percent chance may be a "pretty even chance",
80 percent or so may mean a "very good chance",
and a 98 or 99 percent chance may be "almost certain"

Next

What do you think is the percent chance that you will vote in this year's election for governor?

Type in the number for the answer

[ ] %

Next

If you do vote in this year's election for governor, what do you think is the percent chance that you will vote for the following candidates:

Type in the answer into each cell in the grid

	%
John Kitzhaber (Democrat)	
Chris Dudley (Republican)	
Someone else	
Total	0

Note: This question asks about your chances of voting for the different candidates; it is not the same question as the previous one on predicting vote shares.

Next

DOV: VOTES

Select one answer only

- 1000
- 100

Next

What do you think is the percent chance the election for governor will be decided by 1000 or fewer votes?

Type in the number for the answer

[ ] %

Next

Below are the results of a recent poll about the race for governor. The poll was conducted over-the-phone by a leading professional polling organization. People were interviewed from all over the state, and the poll was designed to be both non-partisan and representative of the voting population. Polls such as these are often used in forecasting election results.

Of people supporting either the Democratic or Republican candidates, the percent supporting each of the candidates were:

John Kitzhaber (Democrat):	**51%**
Chris Dudley (Republican):	**49%**

Next

We would like to again ask you some of the same questions we did above:

Next

In the election for governor, of the people voting for either the Democatic or Republican candidates, what share do you predict will vote for the Democratic candidate and what share do you predict will vote for the Republican candidate?

Type in the answer into each cell in the grid

	%
John Kitzhaber (Democrat)	
Chris Dudley (Republican)	
Total	0

Recent Poll Results:

John Kitzhaber (Democrat):	**51%**
Chris Dudley (Republican):	**49%**

Next

What do you think is the percent chance that you will vote in this year's election for governor?

Type in the number for the answer

[ ] %

Recent Poll Results:

John Kitzhaber (Democrat):	**51%**
Chris Dudley (Republican):	**49%**

Next

If you do vote in this year's election for governor, what do you think is the percent chance that you will vote for the following candidates:

Type in the answer into each cell in the grid

	%
John Kitzhaber (Democrat)	
Chris Dudley (Republican)	
Someone else	
Total	0

Recent Poll Results:

John Kitzhaber (Democrat):	**51%**
Chris Dudley (Republican):	**49%**

Next

What do you think is the percent chance the election for governor will be decided by 1000 or fewer votes?

Type in the number for the answer

[ ] %

Recent Poll Results:

John Kitzhaber (Democrat):	**51%**
Chris Dudley (Republican):	**49%**

Next

What do you think is the percent chance the election for governor will be decided by 1000 or fewer votes?

Type in the number for the answer

[   ] %

Recent Poll Results:

John Kitzhaber (Democrat):	**51%**
Chris Dudley (Republican):	**49%**

Next

Thinking about this topic, do you have any comments you would like to share?

Any comments welcome!

Next

The variables on this screen are select demographic and other data that will be imported into the questionnaire by the system. These questions will be re moved prior to fielding and will NOT be visible to the respondents. They are shown here only for testing purposes. If this survey's functionality depends on some or all of these variables, please enter the appropriate values here.

State - numeric

Type in the number for the answer

92

XPIVOTAL

Select one answer only

- (•) Treatment1
- ( ) Treatment2
- ( ) Control

XSHOW

Select one answer only

- (•) Show Democrat first
- ( ) Show Republican first

Next

DOV: Stateside

Select one answer only

- ○ California
- ○ Texas
- ○ New York
- ○ Florida
- ○ Illinois
- ○ Ohio
- ○ Pennsylvania
- ○ Wisconsin
- ○ Georgia
- ○ Maryland
- ◉ Oregon
- ○ Connecticut
- ○ New Hampshire

Next

Imagine you had a fair coin that was flipped 1,000 times. What do you think is the percent chance that you would get the following number of heads:

Type in the answer into each cell in the grid

	%
Between 0 and 200 heads:	
Between 201 and 400 heads:	
Between 401 and 480 heads:	
Between 481 and 519 heads:	
Between 520 and 599 heads:	
Between 600 and 799 heads:	
Between 800 and 1,000 heads:	
Total	0

Please make sure your answers add up to 100 percent. Also, please try not to spend more than 1 minute on this question.

Next