Supplementary Information for:
Projecting confidence: How the probabilistic horserace confuses and demobilizes the public

Contents

1 Background and additional data measuring the reach of probabilistic forecasts

Data used to measure the 2016 reach of probabilistic forecasts span the period from 8/1/2016 to 11/7/2016 (the day before the election).

Panel A uses data from the Internet Archive's Television Archive. We conducted a search for several terms related to election probabilities:

- "538"
- "nate silver"
- "probability of winning"
- "chance of winning"

These queries were selected based on exploration of the data. Each cable news audience was coded as liberal/conservative using data from Mitchell, Gottfried, Kiley, and Matsa (2014); Bakshy, Messing, and Adamic (2015). The names of other probabilistic forecasters were not used in queries because they were either captured with other queries or were not covered on cable news.

Panel B uses data from comScore. ComScore maintains a panel of approximately 30,000 internet users and monitors their web traffic. These numbers are used to estimate overall web traffic by a expansive set of marketing and content companies. We queried data for probabilistic forecasters (including FiveThirtyEight), NYTimes.com and Breitbart.com. ComScore data cannot be queried below the domain-level, so were are unable to separate general traffic to each website from the specific sections of the websites reporting election information. Figure A1 presents a similar analysis using an alternative measure from Alexa.

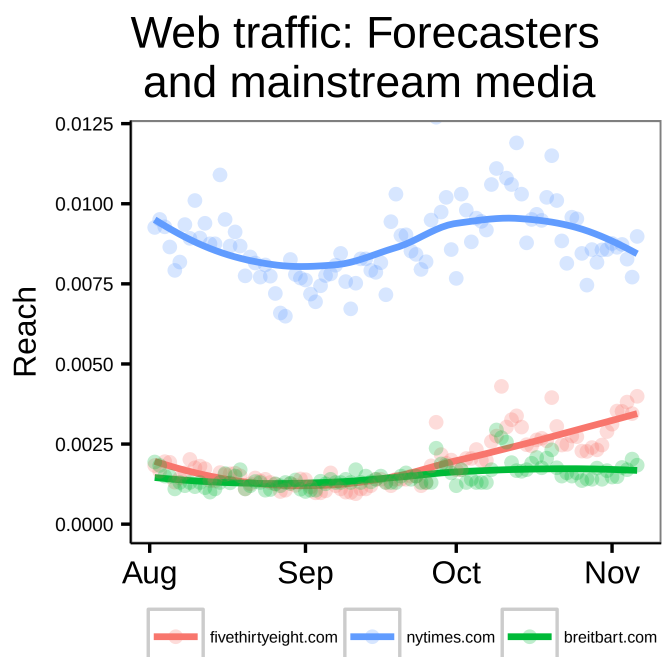


Figure A1: An alternative to comScore, Alexa web traffic data shows similar patterns with at least one probabilistic forecaster attaining traffic levels approaching that of news media outlets.

Panel C uses data from Twitter collected via Gnip. We queried for tweets containing a link to specific sections of websites where probabilistic forecasts were presented. [1]

URLs containing the following links to probabilistic forecasts and collections of polling data were used to query for Tweets created from 8/1/2016 to 11/7/2016:

[1] Although links are commonly shortened on Twitter, Gnip attempts to expand these shortened links for broader coverage. More information is available at http://support.gnip.com/enrichments/expanded_urls.html

- projects.fivethirtyeight.com/2016-election-forecast/
- www.realclearpolitics.com/epolls/2016/president/2016_elections_electoral_college_map.html
- www.nytimes.com/interactive/2016/upshot/presidential-polls-forecast.html
- www.nytimes.com/interactive/2016/us/elections/polls.html
- elections.huffingtonpost.com/2016/forecast/president
- elections.huffingtonpost.com/pollster/2016-general-election-trump-vs-clinton
- elections.dailykos.com/app/elections/2016
- election.princeton.edu/

Panel D uses Google search query data from the same period.

- Probabilistic forecasters (”princeton election consortium” + ”five thirty eight” + ”fivethirtyeight” + 538 + ”new york times election forecast” + ”huffington post election forecast” + ”dailykos election forecast”)
- New York Times
- Breitbart

The top part of this panel shows search for each of these three groups by state. States are colored such that they correspond to the largest source of searches. The bottom part of this panel shows the quantity of searches over time for the three groups. According to Google, values “represent search interest relative to the highest point on the chart for a given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise a score of 0 means the term was less than 1% as popular as the peak.” See https://trends.google.com for more detail.

Google News Index We searched Google News for mentions of probabilistic forecasts using the query: `fivethirtyeight OR "princeton electoral consortium" OR "nate silver" OR "probability of winning" OR "election forecast"`. It should be noted that Google News does not return the exact same number of results over time, so these numbers should be considered approximations.

The number of articles returned by Google News follows:

Year	# of articles
2008	907
2012	3,860
2016	15,500

Data collected on January 30, 2018 from https://goo.gl/5JhVHU, https://goo.gl/Cj7pTo, and https://goo.gl/qpP2wa. To view the result count, users may need to click on the "tools" button in their browser.

Table A1 shows "alignment" scores, based on ideology of audience sharing content from each domain on Facebook, (Bakshy, Messing, and Adamic 2015) for key websites hosting poll aggregators. The sites hosting probabilistic forecasts have a liberal alignment. The only site with conservative alignment is realclearpolitics.com, which does not prominently feature probabilistic forecasts.

Table A1: "Alignment" score, based on ideology of audience sharing content from each domain on Facebook, (Bakshy, Messing, and Adamic 2015) for key websites hosting poll aggregators. The sites hosting probablistic forecasts have a liberal alignment. The only site with conservative alignment is realclearpolitics.com, which does not prominently feature probabilistic forecasts.

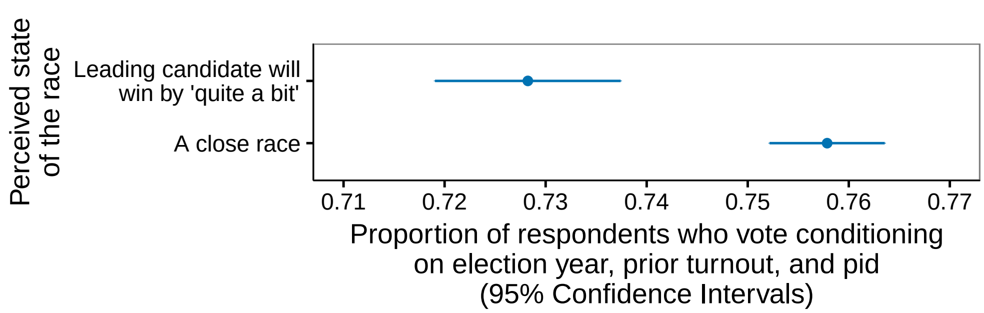
domain	avg_align
fivethirtyeight.com	-0.5225
www.nytimes.com	-0.5469
www.huffingtonpost.com	-0.6176
www.realclearpolitics.com	0.6616

2 Perceptions of closeness and turnout: 1952-2016

In this section we analyze data collected by the American National Election Study (ANES) to shed additional light on the relationship between perceptions of closeness, turnout, and party identification. This section shows that from 1952-2016, (1) people who say that one candidate will "win by quite a bit" in pre-election polling were less likely to vote; (2) that in 2016 more people said they expected one candidate to "win by quite a bit" compared to recent elections; and (3) that in 2016 Democrats were more likely to say this than Republicans, compared to recent elections.

Relationship between closeness and turnout Table A2 shows a robust relationship between perceptions that the winning candidate will win by "quite a bit," and lower levels of turnout. This relationship remains robust after conditioning on year, party, past voting, and actual electoral closeness (measured based on the absolute value of the margin of the popular vote and the electoral college). The coefficient remains approximately the same in a multi-level model with random intercepts for each year and random slopes for popular- and electoral college absolute vote margins.

Figure A2



Members of the public saying that they expect one candidate to "Win by quite a bit" in pre-election polling by the American National Election Study are less likely to vote, even after conditioning on year, party, past voting (predicted proportions from model 4 in Table A2.

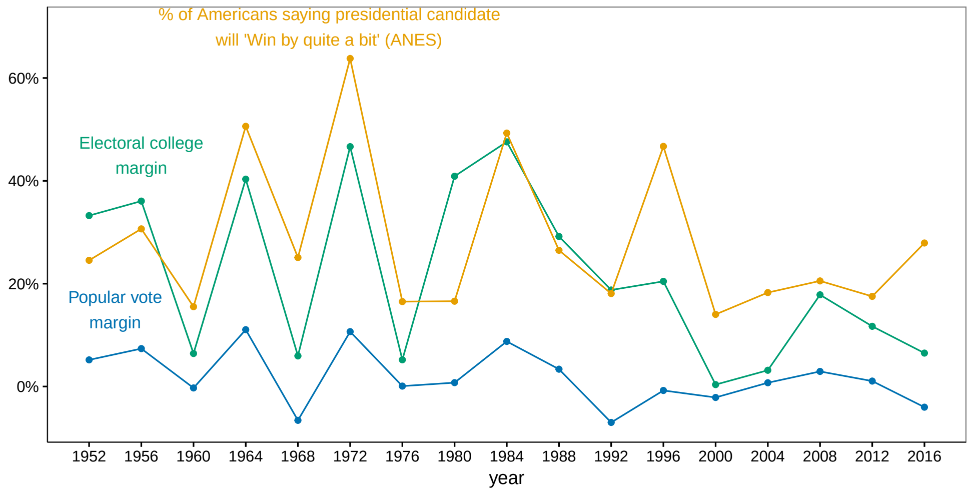
Perceptions of closeness over time **?** raised concerns that the rise of the probabilistic horse race may be giving the public unusually confident impressions that one candidate will win. Unfortu-

Table A2: The robust relationship between perceptions of closeness and turnout, 1952 - 2016. Note: Model 4 contains fixed effects for year.

	Dependent variable:			
	Voted			
	(1)	(2)	(3)	(4)
'Win by quite a bit'	-0.037^{***}	-0.024^{***}	-0.030^{***}	-0.024^{***}
	(0.006)	(0.005)	(0.006)	(0.006)
Prior turnout		0.448^{***}	0.448^{***}	0.448^{***}
		(0.005)	(0.005)	(0.005)
Independent		-0.115^{***}	-0.112^{***}	-0.104^{***}
		(0.009)	(0.009)	(0.009)
Lean dem		0.0002	0.003	0.003
		(0.009)	(0.009)	(0.009)
Lean rep		0.015	0.017	0.021^{*}
		(0.009)	(0.009)	(0.009)
Rep		0.023^{**}	0.024^{**}	0.027^{**}
		(0.009)	(0.009)	(0.009)
Strong dem		0.044^{***}	0.045^{***}	0.050^{***}
		(0.008)	(0.008)	(0.008)
Strong rep		0.067^{***}	0.069^{***}	0.074^{***}
		(0.009)	(0.009)	(0.009)
Electoral college margin			0.092^{***}	
			(0.021)	
Popular vote margin			0.0004	
			(0.093)	
Constant	0.751^{***}	0.425^{***}	0.407^{***}	0.462^{***}
	(0.003)	(0.007)	(0.008)	(0.012)
Observations	31,937	23,922	23,922	23,922
R^2	0.001	0.257	0.258	0.266
Adjusted R^2	0.001	0.256	0.257	0.266
				$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

nately, that analysis was based on a flaw in the ANES cumulative data file. However, 2016 did see a higher proportion of the public saying that they expect one candidate to ”Win by quite a bit” in pre-election polling by the American National Election Study (Figure A3) than in many recent elections.

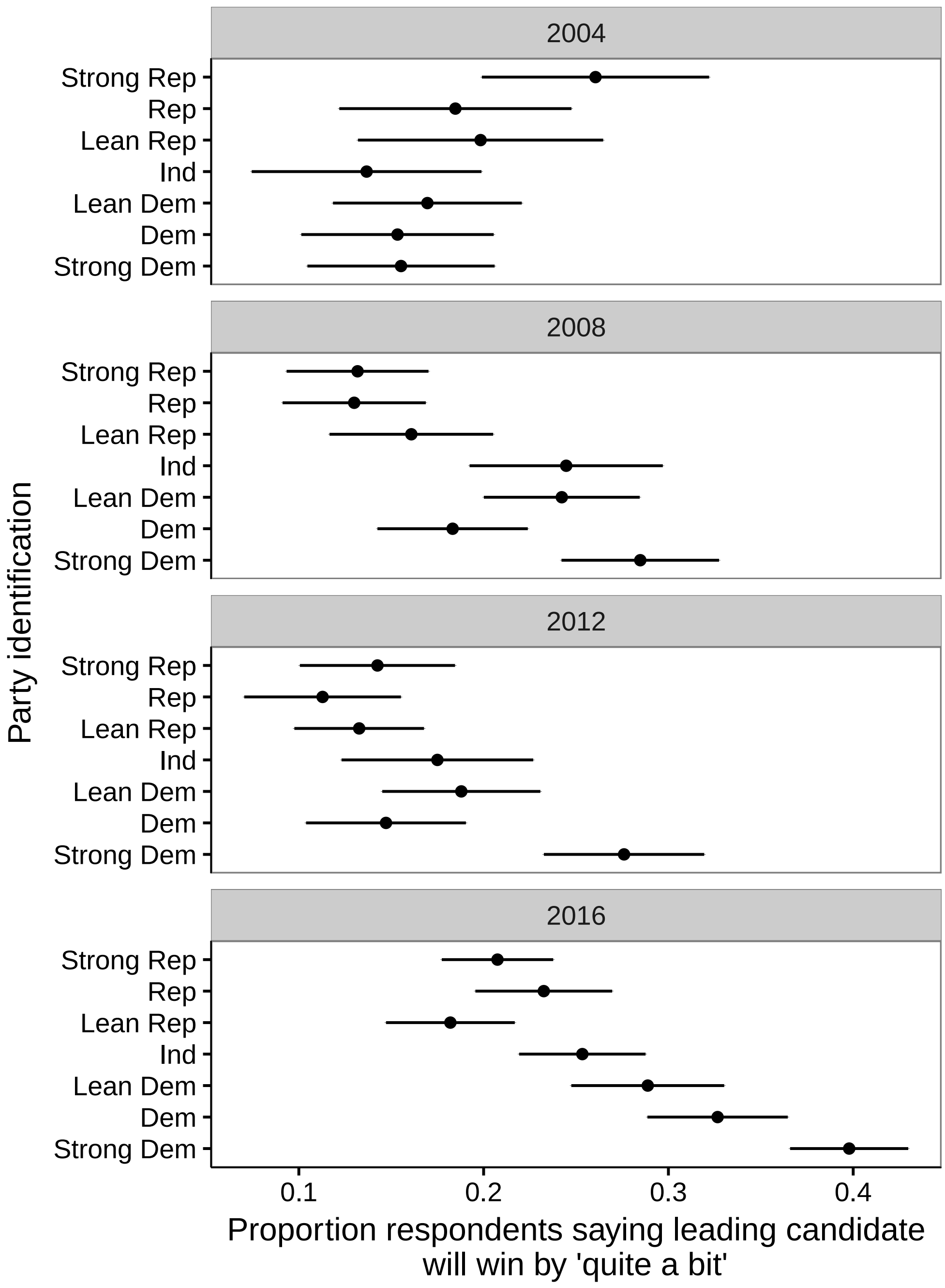
Figure A3: Public expectations of large victories in presidential elections, 1952-2016



The proportion of the public saying that they expect one candidate to ”Win by quite a bit” in pre-election polling by the American National Election Study (orange) rose in 2016 compared to recent elections, while the popular vote (blue) and electoral college vote margins (green) declined slightly.

In addition, 2016 saw the most lopsided imbalance by party in perceptions of whether one candidate would win by “quite a bit” in recent election years, as shown in Figure A4.

Figure A4: 2016 saw large imbalance in proportion of Democrats and Republicans who thought one candidate would "win by quite a bit."



3 Study 1: Perceptions of probabilistic forecasts

3.1 Design

On wave 25 of the American Trends Panel, participants were presented with an experiment. As explained in the main text, this consisted of a hypothetical election for the U.S. Senate,[2] in which Candidate A "supports the majority of the policies you support and is well qualified for the job." Participants were told "Candidate B does not share your views and is less qualified than Candidate A." They were then shown one of ten hypothetical aggregated survey estimates, which were presented as either as the average vote share, probability of winning, or both, based on random assignment, see also Table A3.

		CI displayed	
Condition	Display order	No	Yes
Vote share	Only one display	813	818
P(win)	Only one display	875	0
Both	P(win) first	423	410
	Vote share first	413	399

Table A3: Assignment to conditions governing what information participants encountered in Study 1. Each participant was independently randomly assigned to a projection Candidate A's vote share that varied from 45% to 55%, with a 95% CI of +/-2%, and corresponding estimates of the probability that A will win (e.g., will have support greater than 50%) that ranged from 13% to 87%.

For ease of interpretation, we pooled across two additional factors in the main text, though we present the full results in Tables A9 and A8, below. Among conditions displaying the vote share, a margin of error of +/-2% was displayed for half of participants in those conditions. Among conditions displaying both the vote share and the win-probability, half were randomly assigned to see the vote share appear first, half to see the win-probably first. Displaying the margin of error had no effect on judgments about the state of the race or certainty. Displaying the win-probability

[2] The fact that this is a Senate race might induce some people to wonder whether the survey error might be substantially higher than in a typical presidential race, such that a high win probability would mean a sharper difference in vote share than what we present here. However, we find little evidence that respondents were considering survey error in formulating their responses, based on the fact that presenting the margin of error alongside the vote share had no effect on any outcome.

Table A4: Study 1 Values

Estimate	Margin of Error	Probability
0.45	0.02	0.13
0.46	0.02	0.19
0.47	0.02	0.25
0.48	0.02	0.33
0.49	0.02	0.41
0.51	0.02	0.59
0.52	0.02	0.67
0.53	0.02	0.75
0.54	0.02	0.81
0.55	0.02	0.87

first resulted in slightly more extreme estimates of Candidate A's likelihood of victory and slightly more certainty about those judgments (See Table A8).

Estimates of Candidate A's vote share were randomly assigned to values ranging from 45% to 55%. A plausible margin of error (95% CI) of +/-2% for these aggregated vote share estimates was generated by simulating 20 surveys of 1000-people at varying levels of support (see simulation below), and taking the average. Based on that error, estimates of the probability that candidate A would win were then randomly assigned to values ranging from 13% to 87%. For context, the final election day New York Times forecast estimated that Clinton's chances of winning the 2016 presidential election were 85%, which corresponded to winning 57.8% of the electoral vote share **?**.

3.1.1 Simulation of survey data

The simulation assumes a total survey error framework, in which each survey has sampling error and survey-specific error, which could be due to (uncorrected) biased sampling/weighting, question wording issues, attention decay, mode effects. This varies normally across surveys. Each survey then draws a sample of 1000 people and support for Candidate A is estimated using on the average (no weighting or modeling is employed).

With this data in hand, the probability of victory, or $P(\mu_v > .5)$ can be estimated by $1 -$

$\Phi\left(\frac{\hat{\mu}_v - .5}{\hat{\sigma}_v}\right)$.[3] The simulation follows:

```
set.seed(25)


# "Actual" vote share:
vote_share <- seq(from= .45, to = .55, by = .01)


# surveys
N_survey <- 20


# Non-sampling error parameter,
# (e.g., biased sampling/weighting,
# question wording, attention decay, mode effects, etc.,)
# see MAE checks below
survey_noise_sd = .04


# variables to fill in
mae_check <- numeric(length(vote_share))
est <- numeric(length(vote_share))
est_se <- numeric(length(vote_share))


for(vs in 1:length(vote_share)){


  # generate survey-noise
  survey_noise <- rnorm(n = N_survey, sd = survey_noise_sd)
```

[3] Alternatively non-parametric estimates based on simulation such as $\frac{1}{J}\sum_j^J I(\hat{\mu}_{v(j)} > .5)$ can be used to estimate the probability of victory, which is particularly useful for example when drawing J simulated electoral college outcomes. Similarly, the vote share and standard error thereof can be estimated by taking the average and standard deviation of $\hat{\mu}_{v(j)}$.

```
  # draw respondents from 20 surveys
  n <- 1000

  # the survey specific error parameter
  p <- vote_share[vs] + survey_noise

  mae_check[vs] <- mean(abs(p - vote_share[vs]))

  # for each survey, generate sample of respondents,
  # say that a "1" expresses support for Candidate A,
  # compute average support "measured" in the survey
  svy <- numeric(length(p))
  for(i in 1:length(p)){
    svy[i] <- mean(rbinom(n = n, size = 1, prob = p[i]))
  }

  # Compute the aggregated average support for A (grand mean)
  # and standard error of the grand mean.
  est[vs] <- mean(svy)
  est_se[vs] <- sqrt(var(svy)/N_survey)

}

mean(mae_check)

# Take the average, now we have a reasonable SE
```

```
# (cleaner treatments if variance is constant across cells)
est_se <- mean(est_se)


# Remove .5
est_vote_share <- vote_share[-6]


# Compute CIs for each estimate using T distribution
CI_mult <- qt(.975, df = N_survey)
CI <- CI_mult * est_se


# and corresponding estimate of the probability that A's
# "true" support is greater than 50\%
est_prob <- 1-pnorm(q = .5, mean = est_vote_share, sd = est_se * sqrt(N_survey) )
```

Values shown to participants are in Table A4.

3.1.2 Hypothetical election vignette

Participants were then presented with the following prompt:

> Please read the following statement about a hypothetical election for the U.S. Senate. There are two candidates.
>
> Candidate A supports the majority of the policies you support and is well qualified for the job. Candidate B does not share your views and is less qualified than Candidate A.
>
> A prominent group of statisticians analyzed the 10 most recent polls that include questions about who voters prefer. Their analysis a few days before the election shows that Candidate A [has a `est_prob` percent chance of victory OR is expected to win `est` percent of the vote {included for random half: +/- `CI`} OR {both statements, order randomly assigned}].

3.1.3 Question wording

CERTWIN Based on this information, how certain or uncertain are you that candidate A will win or lose the election?

1. Very certain
2. Somewhat certain
3. Neither certain nor uncertain
4. Somewhat uncertain
5. Very uncertain

LIKELYWIN If you had to guess, on a scale from 0 to 100, how likely is candidate A to win the election?

[Enter number between 0 and 100]

SOFT PROMPT TEXT IF LEFT BLANK: "We'd like your best guess."

HARD PROMPT TEXT IF INVALID CHARACTER: "Please enter just a number with no characters like a decimal or % sign."

HARD PROMPT TEXT IF INVALID RANGE: "Please enter a number between 0 and 100."

PRCNTVT If you had to guess, on a scale from 0 to 100, what percent of the vote do you expect candidate A to get?

[Enter number between 0 and 100]

SOFT PROMPT TEXT IF LEFT BLANK: "We'd like your best guess."

HARD PROMPT TEXT IF INVALID CHARACTER: "Please enter just a number with no characters like a decimal or % sign."

HARD PROMPT TEXT IF INVALID RANGE: "Please enter a number between 0 and 100."

VOTEHYPO How likely would you be to vote in this election?

1. Very likely

2. Somewhat likely

3. Somewhat unlikely

4. Very unlikely

3.2 Sample

Our data consist of 4,151 participants who completed a survey experiment embedded in Pew Research Center's American Trends Panel. This study was fielded in April of 2017.

As stated on the Pew Research Center website, the American Trends Panel (ATP), created by the Pew Research Center, is a nationally representative panel of randomly selected U.S. adults recruited from landline and cell phone random digit dial surveys. Panelists participate via monthly self-administered Web surveys. Panelists who do not have internet access are provided with a tablet and wireless internet connection. The panel is being managed by Abt Associates. Additional recruitment details are provided here http://www.pewresearch.org/methodology/u-s-survey-research/american-trends-panel/. Because we are estimating sample average treatment effects rather than population average treatment effects **??**, survey weights are not used in this analysis.

3.2.1 Sample descriptives

3.3 Additional results from Study 1

Full regression results Table A6 presents the ordinary least squares results for Study 1. Based on Figure 2 in the main text the effects on certainty appear far stronger when Candidate A is in the lead, as should be expected based on motivated reasoning—recall that participants were told Candidate A is more competent and shares their views on a range of issues. Hence, in the fourth column of Table A6, we present results on the subset of respondents who were told that Candidate A was in the lead.

Robustness check: participants who may have confused probabilistic estimates and vote share We present the results from the models above after removing participants who reported

Table A5: Sample Information for Study 1

	Overall
n	4151
Gender = Female (%)	2093 (50.4)
Race (%)	
White/Caucasian	3205 (77.2)
African American	320 (7.7)
Hispanic	317 (7.6)
Other	261 (6.3)
Age (%)	
18-34	784 (18.9)
34-54	1275 (30.7)
55+	2088 (50.3)
Education (%)	
HS or Less	624 (15.0)
Some College	1322 (31.8)
College+	2205 (53.1)

Table A6: Main results, Study 1

	Dependent variable:			
	% of vote	Likely to win	Certainty	Certainty (Share >50%)
	(1)	(2)	(3)	(4)
Estimate	0.368***	0.530***		
	(0.099)	(0.125)		
Condition: Both	−0.276***	−0.619***	0.034***	0.062***
	(0.070)	(0.089)	(0.008)	(0.011)
Condition: Probability	−0.740***	−1.108***	0.067***	0.102***
	(0.084)	(0.106)	(0.010)	(0.013)
Est × Cond: Both	0.554***	1.232***		
	(0.140)	(0.177)		
Est × Cond: Prob	1.493***	2.202***		
	(0.167)	(0.211)		
Intercept	0.362***	0.304***	0.555***	0.571***
	(0.050)	(0.063)	(0.006)	(0.008)
Observations	4,123	4,120	4,133	2,132
R^2	0.066	0.103	0.012	0.032
Adjusted R^2	0.065	0.102	0.012	0.031
Note:				*p<0.05; **p<0.01; ***p<0.001

they anticipated Candidate A's vote share to be within 1% of the win-probability provided, and so may have confused probabilistic estimates and vote share in figure A7.

Table A7: Removing participants who may have confused probabilistic estimates and vote share.

	Dependent variable:			
	% of vote	Likely to win	Certainty	Certainty (Share >50%)
	(1)	(2)	(3)	(4)
Estimate	0.339***	0.518***		
	(0.097)	(0.125)		
Condition: Both	−0.246***	−0.611***	0.035***	0.065***
	(0.069)	(0.089)	(0.008)	(0.011)
Condition: Probability	−0.491***	−0.904***	0.067***	0.099***
	(0.085)	(0.108)	(0.010)	(0.013)
Est × Cond: Both	0.495***	1.219***		
	(0.138)	(0.177)		
Est × Cond: Probability	1.013***	1.806***		
	(0.169)	(0.216)		
Intercept	0.376***	0.310***	0.554***	0.569***
	(0.049)	(0.063)	(0.006)	(0.008)
Observations	4,003	3,991	3,990	2,053
R^2	0.046	0.088	0.012	0.031
Adjusted R^2	0.045	0.087	0.012	0.031
Note:				*p<0.05; **p<0.01; ***p<0.001

Primacy effects For simplicity of presentation, Table A6 pools conditions that presented both a probabilistic estimate and a vote share estimate in different order. However, order did have a modest impact on the outcomes analyzed above, consistent with a primacy effect—if probabilistic forecasts were displayed first, participants tended to state that the results would be more lopsided for the winning candidate. Hence, in Table A8 we present models with both estimates, with order disaggregated.

Table A8: Analysis of order when probability and vote share displayed

	Dependent variable:			
	% of vote	Likely to win	Certainty	Certainty (Share >50%)
	(1)	(2)	(3)	(4)
Estimate	1.114***	1.972***		
	(0.130)	(0.175)		
Vote share first	0.195*	0.214	−0.003	−0.034*
	(0.093)	(0.125)	(0.011)	(0.015)
Est × share first	−0.390*	−0.426		
	(0.185)	(0.249)		
Intercept	−0.010	−0.421***	0.590***	0.649***
	(0.065)	(0.088)	(0.008)	(0.010)
Observations	1,633	1,632	1,639	849
R^2	0.060	0.111	0.00003	0.006
Adjusted R^2	0.058	0.109	-0.001	0.005
Note:				*p<0.05; **p<0.01; ***p<0.001

The (null) effect of seeing the margin of error When participants were assigned to see any "vote share" condition, half were randomly assigned to see the margin of error, a 95% confidence interval, associated with each estimate (Table A9). However, this had no effect on the outcomes examined above that was distinguishable from noise.

We also asked participants how likely they would be to vote in this hypothetical election. However, because nearly all participants said they would vote—only 6% of participants said they would be somewhat or very unlikely to vote in said election—we have very limited power to detect an effect with these data. With the addition of control variables—party and whether the respondent reported voting in 2016, we observe weak evidence ($p = 0.11$, two-tailed) of lower self-reported turnout when Candidate A has a stronger lead and the hypothetical survey results are presented in terms of win probability (Table A10).

While we found some limited evidence of a negative effect of probabilistic presentation on self-reported hypothetical turnout when candidate A had a stronger lead, unlike study 2 this design is not well-suited to test that question—the cost of reporting the (socially desireable) intent to

Table A9: Inclusion of Margin of Error

	Dependent variable:			
	% of vote	Likely to win	Certainty	Certainty (Share >50%)
	(1)	(2)	(3)	(4)
Estimate	0.420**	0.460**		
	(0.134)	(0.174)		
Condition: Both	−0.314**	−0.652***	0.028*	0.067***
	(0.095)	(0.124)	(0.011)	(0.015)
Condition: MOE	0.064	−0.053	−0.002	0.011
	(0.095)	(0.123)	(0.011)	(0.016)
Est × Both	0.628***	1.302***		
	(0.190)	(0.247)		
Est × MOE	−0.108	0.130		
	(0.189)	(0.245)		
Both × MOE	0.069	0.059	0.012	−0.012
	(0.134)	(0.174)	(0.016)	(0.022)
Est × Both × MOE	−0.133	−0.125		
	(0.267)	(0.346)		
Intercept	0.331***	0.333***	0.556***	0.565***
	(0.067)	(0.087)	(0.008)	(0.011)
Observations	3,252	3,250	3,261	1,680
R^2	0.035	0.066	0.006	0.019
Adjusted R^2	0.033	0.064	0.005	0.017
Note:				*p<0.05; **p<0.01; ***p<0.001

Table A10: Analysis of hypothetical self-reported vote intent

	Dependent variable:		
	Vote intent self report		
	(1)	(2)	(3)
Estimate	−0.008	0.290	0.299
	(0.508)	(0.410)	(0.410)
Condition: Both	0.191	0.266	0.279
	(0.361)	(0.292)	(0.292)
Condition: Probability	0.218	0.515	0.518
	(0.432)	(0.348)	(0.348)
Reported voting in 2016		0.191***	0.190***
		(0.004)	(0.004)
Republican			0.031
			(0.022)
Democrat			0.041*
			(0.020)
Est × Cond: Both	−0.373	−0.494	−0.519
	(0.719)	(0.581)	(0.581)
Est × Cond: Probability	−0.433	−1.109	−1.115
	(0.861)	(0.694)	(0.693)
Intercept	3.706***	1.805***	1.792***
	(0.255)	(0.210)	(0.210)
Observations	4,138	3,781	3,781
R^2	0.0002	0.369	0.369
Adjusted R^2	-0.001	0.368	0.368
Note:			*p<0.05; **p<0.01; ***p<0.001

vote is extremely low and only 6% of participants claimed they would be unlikely to vote in the hypothetical election.

3.4 Additional survey experiments

3.4.1 Office of the hypothetical candidate

One concern with Study 1 is that we used hypothetical candidates for the US Senate. It is possible that participants perceived state-level polling (and computed probabilities) as nosier and less credible than the national polling used in presidential forecasts. Using a sample from Mechanical Turk (N=275) we replicated Study 1 and varied the office of the candidates (U.S. House/U.S. Senate/U.S. President). To simplify this study we only used two of the twenty numerical values for probability/vote share (45% and 55%). We find that there are no differences in responses by the office sought by the hypothetical candidates (see Table A11).

Table A11: Office doesn't matter when assessing probabilities

	Dependent variable:		
	Certainty	Likelihood of Winning	Expected Vote Share
	(1)	(2)	(3)
President	−0.027	−0.703	−0.675
	(0.047)	(4.133)	(2.634)
House	−0.031	−1.717	−2.901
	(0.047)	(4.114)	(2.621)
Constant	0.564***	58.398***	56.096***
	(0.035)	(3.020)	(1.924)
Observations	274	275	275
R^2	0.002	0.001	0.005
Adjusted R^2	−0.006	−0.007	−0.002
Residual Std. Error	0.314 (df = 271)	27.511 (df = 272)	17.528 (df = 272)
F Statistic	0.246 (df = 2; 271)	0.089 (df = 2; 272)	0.692 (df = 2; 272)
Note:			*p<0.05; **p<0.01; ***p<0.001

3.4.2 Which candidate is reported as ahead

We find that participants engage in wishful thinking when evaluating candidates that are aligned with their preferences. We ran a replication of Study 1 (using the Qualtrics Panel) where we varied the candidate reported to be ahead or behind. In addition to varying the candidate on which information would be provided, the numerical values were randomly varied: 41% chance of victory or 58% chance of victory. Results (Table A12) show that participants responded differently when their candidate was reported to win/lose compared to when the other candidate was reported to win/lose.

Table A12: Randomizing which candidate is reported as ahead

	Dependent variable:		
	Certainty	Vote Share	Probability of Victory
	(1)	(2)	(3)
Candidate B Ahead	0.092	1.604	7.025
	(0.052)	(4.238)	(4.772)
Winning Probability	0.048	6.249	8.412
	(0.052)	(4.278)	(4.817)
Candidate B Ahead X Winning Probability	-0.190^{**}	-13.204^{*}	-15.220^{*}
	(0.072)	(5.871)	(6.592)
Intercept Average	0.642^{***}	60.730^{***}	59.892^{***}
	(0.039)	(3.185)	(3.586)
Observations	177	176	177
R^2	0.051	0.046	0.030
Adjusted R^2	0.035	0.029	0.014
Residual Std. Error	0.237 (df = 173)	19.374 (df = 172)	21.811 (df = 173)
F Statistic	3.108^{*} (df = 3; 173)	2.772^{*} (df = 3; 172)	1.809 (df = 3; 173)
Note:			*p<0.05; **p<0.01; ***p<0.001

4 Study 2: Behavioral economic voting game

4.1 Design

Participants were first told:

> "You will now play a series of games. We will start you off with a wallet of $15.
>
> You will play a game with other people taking this survey. This game is about voting. Before each round you will be grouped with other players and randomly assigned to one of two teams: Team A or Team B.
>
> Voting for your team increases the chance that your team will win. A vote costs $1 from your wallet. If your team wins you will be paid $2. If your team loses you will be charged $2. You will be paid or charged regardless of whether you vote, though if you don't vote it is less likely that your team will win.
>
> In each round you and the other players will answer a poll on how you intend to vote. Based on this poll, as well as information from prior games, we will calculate the chance that your team will win. To help you decide how to vote, we will show you this probability as well as the results of the poll."

They were then asked a series of followup questions and told the correct answer to ensure understanding:

- "How much does it cost to vote?" $0, **$1**, $2, $5
- "If you don't vote and your team wins, how much will you be paid?" $0, $1, **$2**, $3
- "If you vote and your team wins, how much will you be paid?" $0, $1, **$2**, $3
- "The outcome of each round is determined by:" **How many people vote for each team**, Randomly

- “How do we calculate the chance that your team will win?” **Using polling data and outcomes from prior games**, Polling data, Results from prior games, Random chance

- “Voting for your team:” **Increases the chance that your team will win**, Decreases the chance that your team will win, Has no effect on the outcome

Participants then saw the following:

> “Consider the following example: If you were assigned to Team A.
>
> survey/i1.png
>
> 1) You would first have a chance to report in a Poll if you plan to vote or not vote. [Example poll displayed]
>
> survey/i2.png
>
> 2) We would then tally the poll and show you how we predict the round to end. You can then decide if you want to vote for Team A, Team B or not vote. [Example decision page displayed]

survey/i3.png

3) We would then report the final result. If the most votes went to Team A you would win:

survey/i4.png

However, if the most votes went to Team B you would lose:

survey/i5.png

"

Participants were then asked if they would like to see the instructions one more time or start the game. If the latter, they saw the following:

“Waiting for other survey respondents The game will automatically start as soon as enough participants have entered the lobby. Please wait a moment”

Participants then were randomly assigned to either Team A or B.

They were then asked: “For this round do you plan to:” Vote for your team or Not vote

Participants then were told to “Please wait a moment for others to decide,” they then saw a result like the following:

survey/i3.png

Finally, based on their response to the poll and the randomly assigned outcomes, they saw similar feedback:

survey/i4.png

This was then repeated five times.

4.1.1 Payments

Participants were paid the balance of their wallet (a 10% multiplier applied) at the end of the game. This compensation was offered in addition to the base payment they received for completing the survey.

4.2 Sample

Table A13 shows information on the sample for study 2. The sample was drawn to approximate census values for race/ethnicity, gender and age.

Table A13: Sample Information for Study 2

	Overall
n	1171
Gender = Female (%)	579 (49.4)
Race (%)	
White/Caucasian	851 (72.7)
African American	118 (10.1)
Hispanic	121 (10.3)
Other	81 (6.9)
Age (%)	
18-34	346 (29.5)
34-54	418 (35.7)
55+	407 (34.8)
Education (%)	
HS or Less	242 (20.7)
Some College	433 (37.0)
College+	496 (42.4)

4.3 Additional results

Table A14 reports the model results used to generate Figure 3 in the main manuscript. The model includes participant-level random intercepts. Also notable is the fact that respondents were less likely to vote in later rounds than earlier rounds. This is suggestive that respondents learn that they do not necessarily need to vote to reap the benefits of their team winning and can conserve resources by doing so.

Table A14: Model results for Study 2

	Dependent variable:
	voted
abs(Midpoint Distance, Probability)	-0.173^{***}
	(0.042)
abs(Midpoint Distance, Vote Share)	-0.132
	(0.188)
Trial 2	-0.124^{***}
	(0.017)
Trial 3	-0.138^{***}
	(0.017)
Trial 4	-0.165^{***}
	(0.017)
Trial 5	-0.166^{***}
	(0.017)
Intercept Average	0.873^{***}
	(0.019)
Observations	5,845
Log Likelihood	$-3,525.870$
Akaike Inf. Crit.	7,069.740
Bayesian Inf. Crit.	7,129.800
Note:	*p<0.05; **p<0.01; ***p<0.001

Table A15: Model results for Study 2, fixed effects for trial and individual. Standard errors clustered at the individual level

	Dependent variable:
	voted
abs(Midpoint Distance, Probability)	-0.186^{***}
	(0.048)
abs(Midpoint Distance, Vote Share)	-0.123
	(0.229)
Observations	1,171
R^2	0.342
Adjusted R^2	0.177
Residual Std. Error	0.413 (df = 4670)
Note:	*p<0.05; **p<0.01; ***p<0.001

It is possible that some people learned that the predictions were inaccurate (random) over time. However, with only five rounds, it would be challenging to detect that predictions were randomly assigned without conducting statistical analysis. Table A17 shows that there were no significant interactions between round and absolute distance, suggesting that on average people did not exhibit this tendency.

Table A16: Model results for Study 2, removing those who mixed up probability and vote share

	Dependent variable:
	voted
abs(Midpoint Distance, Probability)	-0.162^{***}
	(0.046)
abs(Midpoint Distance, Vote Share)	-0.134
	(0.204)
Trial 2	-0.126^{***}
	(0.019)
Trial 3	-0.146^{***}
	(0.019)
Trial 4	-0.172^{***}
	(0.019)
Trial 5	-0.164^{***}
	(0.019)
Intercept Average	0.875^{***}
	(0.021)
Observations	5,007
Log Likelihood	$-3{,}033.890$
Akaike Inf. Crit.	6,085.781
Bayesian Inf. Crit.	6,144.448
Note:	*p<0.05; **p<0.01; ***p<0.001

Table A17: Study 2 Model with Interactions

abs(Midpoint Distance, Probability)	-0.157
	(0.100)
Trial	-0.024^{*}
	(0.011)
abs(Midpoint Distance, Vote Share)	0.541
	(0.444)
abs(Midpoint Distance, Probability) $\times$ Trial	-0.005
	(0.030)
abs(Midpoint Distance, Vote Share) $\times$ Trial	-0.225
	(0.133)
Intercept Average	0.828^{***}
	(0.035)
Random Intercept σ^2	0.032
Observations	5,845
Log-likelihood	$-3,536.4$
AIC	7088.9
BIC	7142.2

It is possible that the effects are not symmetric based on which candidate is ahead. We test for but do not find evidence of asymmetry (Table A18).

Table A18: Study 2 Model testing for directionality

	Dependent variable:	
	voted	
	(1)	(2)
abs(Midpoint Distance, Probability)		-0.178^{***}
		(0.044)
abs(Midpoint Distance, Vote Share)		-0.130
		(0.188)
Probability	0.023	-0.014
	(0.033)	(0.034)
Vote Share	-0.0001	0.0004
	(0.001)	(0.001)
Trial 2	-0.123^{***}	-0.124^{***}
	(0.017)	(0.017)
Trial 3	-0.137^{***}	-0.138^{***}
	(0.017)	(0.017)
Trial 4	-0.164^{***}	-0.165^{***}
	(0.017)	(0.017)
Trial 5	-0.166^{***}	-0.166^{***}
	(0.017)	(0.017)
Intercept Average	0.823^{***}	0.863^{***}
	(0.062)	(0.063)
Observations	5,845	5,845
Log Likelihood	$-3,539.671$	$-3,534.272$
Akaike Inf. Crit.	7,097.343	7,090.544
Bayesian Inf. Crit.	7,157.403	7,163.951
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$	

It is also informative to compare the standardized effects of probability and vote share. This reveals that probability has a much larger effect (Table A19).

Table A19: Study 2, normalized effects

	Dependent variable:
	voted
abs(Midpoint Distance, Probability), Normalized	-0.023^{***}
	(0.006)
abs(Midpoint Distance, Vote Share), Normalized	-0.004
	(0.006)
Trial 2	-0.124^{***}
	(0.017)
Trial 3	-0.138^{***}
	(0.017)
Trial 4	-0.165^{***}
	(0.017)
Trial 5	-0.166^{***}
	(0.017)
Intercept Average	0.827^{***}
	(0.013)
Observations	5,845
Log Likelihood	$-3,531.374$
Akaike Inf. Crit.	7,080.748
Bayesian Inf. Crit.	7,140.808
Note:	*p<0.05; **p<0.01; ***p<0.001

4.4 Numeracy and Probabilities

Table A20: Numeracy has no detectable interaction with the treatment. Trial covariates not shown for ease of interpretation.

	Dependent variable:
	voted
abs(Midpoint Distance, Probability)	-0.197^{***}
	(0.050)
abs(Midpoint Distance, Vote Share)	-0.131
	(0.188)
Numeracy: 33% Correct	-0.037
	(0.029)
Numeracy: 66% Correct	-0.098
	(0.055)
Numeracy: 100% Correct	0.048
	(0.109)
abs(Midpoint Distance, Probability) X Numeracy: 33% Correct	0.099
	(0.101)
abs(Midpoint Distance, Probability) X Numeracy: 66% Correct	0.146
	(0.195)
abs(Midpoint Distance, Probability) X Numeracy: 100% Correct	-0.430
	(0.345)
Intercept Average	0.886^{***}
	(0.021)
Observations	5,845
Log Likelihood	$-3,531.600$
Akaike Inf. Crit.	7,093.200
Bayesian Inf. Crit.	7,193.300
Note:	*p<0.05; **p<0.01; ***p<0.001

5 Study 3: The unimportance of group size in evaluating election probabilities

One important way in which Study 2 differs from a real world election is that the number of voters could be seen as smaller, which means that a person's vote is more likely to be pivotal. Players in the original version of the voting game were not directly told how many other people were playing. Nonetheless, the perceived number of participants was surely lower than in a real world election. Below we present a followup study that explicitly manipulated group size (N) as reported to participants, to gauge whether it attenuated the negative effect of probabilistic forecasts on turnout documented in the main text. The study had 238 participants (1,190 trials) drawn from the Qualtrics Panel.

In this study we gave participants the following instructions: "Many other people are playing this game. Before each round you will be assigned to play with a random group of the total available players." For each round we randomly drew a value from a power of two table: 32, 64, 128, 256 and 512. To make the treatment less obvious we added random noise (drawn between [-3 and 3]) to these values for each round and for each respondent.

We did not find an effect of group N on behavior (Table A21) either in the interaction between group N and probabilities ($\beta = 0.00$, $T = 0.51$, $P = .61$) or in the interaction between group N and vote share ($\beta = -0.00$, $T = -0.78$, $P = .44$). The inclusion of more people does not attenuate these effects—despite the lower likelihood of a pivotal vote all around, we still see similar effects to those in Study 2 above.

5.1 Order of probabilities and vote share

In study 2, the order of probabilities and vote share was fixed (first and second, respectively). It is possible that a primacy or recency effect could bias our attempts to compare the effects of vote share and probabilistic estimates. As part of the followup study varying group N, we randomly varied the order of the information (at the participant-level). There was no effect of order on behavior (Table A21).

Table A21: Group size does not attenuate the effect of probabilistic forecasts; order has no effect detectable in this sample. Trial covariates not shown for ease of interpretation.

	Dependent variable:	
	voted	
	(1)	(2)
abs(Midpoint Distance, Probability)	-0.268^{*}	-0.333^{*}
	(0.137)	(0.163)
abs(Midpoint Distance, Vote Share)	0.303	0.591
	(0.646)	(0.748)
Group Size (N)	0.0001	0.0001
	(0.0002)	(0.0002)
Prob. First	0.047	0.049
	(0.034)	(0.071)
abs(Midpoint Distance, Probability) X Group Size (N)	0.0003	0.0003
	(0.001)	(0.001)
abs(Midpoint Distance, Vote Share) X Group Size (N)	−0.002	−0.002
	(0.002)	(0.002)
abs(Midpoint Distance, Probability) X Prob. First		0.130
		(0.183)
abs(Midpoint Distance, Vote Share) X Prob. First		−0.644
		(0.842)
Intercept Average	0.821^{***}	0.821^{***}
	(0.060)	(0.067)
Observations	1,190	1,190
Log Likelihood	−774.303	−773.797
Akaike Inf. Crit.	1,574.606	1,577.594
Bayesian Inf. Crit.	1,640.668	1,653.819
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$	

Table A22: Small Group sizes also doe not attenuate the effect of probabilistic forecasts; order has no effect detectable in this sample. Trial covariates not shown for ease of interpretation.

	Dependent variable:
	voted
abs(Midpoint Distance, Probability)	-0.339^{*}
	(0.142)
abs(Midpoint Distance, Vote Share)	0.366
	(0.669)
Group Size (7)	-0.016
	(0.074)
Group Size (10)	-0.006
	(0.078)
Group Size (13)	0.036
	(0.077)
Group Size (16)	0.094
	(0.075)
Group Size (19)	0.018
	(0.077)
Group Size (21)	0.028
	(0.076)
Prob. First	-0.011
	(0.024)
abs(Midpoint Distance, Probability) X Group Size (7)	0.197
	(0.203)
abs(Midpoint Distance, Probability) X Group Size (10)	.161
	(0.203)
abs(Midpoint Distance, Probability) X Group Size (13)	-0.194
	(0.202)
abs(Midpoint Distance, Probability) X Group Size (16)	-0.169
	(0.202)
abs(Midpoint Distance, Probability) X Group Size (19)	-0.187
	(0.199)
abs(Midpoint Distance, Probability) X Group Size (21) 1	0.185
	(0.199)
abs(Midpoint Distance, Vote Share) X Group Size (7)	-1.292
	(0.959)
abs(Midpoint Distance, Vote Share) X Group Size (10)	-0.667
	(0.956)
abs(Midpoint Distance, Vote Share) X Group Size (13)	-0.590
	(0.966)
abs(Midpoint Distance, Vote Share) X Group Size (16)	-0.814
	(0.949)
abs(Midpoint Distance, Vote Share) X Group Size (19)	-0.185
	(0.966)
abs(Midpoint Distance, Vote Share) X Group Size (21)	-1.497
	(0.947)
Intercept Average	0.838^{***}
	(0.068)
Observations	3,310
Log Likelihood	$-2,160.378$
Akaike Inf. Crit.	4,376.756
Bayesian Inf. Crit.	4,547.688
Note:	*p<0.05; **p<0.01; ***p<0.001

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