# Projecting confidence: How the probabilistic horserace confuses and demobilizes the public

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**Abstract**

Recent years have seen a dramatic change in horserace coverage of elections in the U.S.—shifting focus from late-breaking poll numbers to sophisticated meta-analytic forecasts that emphasize candidates' chance of victory. Could this shift in the political information environment affect election outcomes? We use experiments to show that forecasting increases certainty about an election's outcome, confuses many, and decreases turnout. Furthermore, we show that election forecasting has become prominent in the media, particularly in outlets with liberal audiences, and show that such coverage tends to more strongly affect the candidate who is ahead—raising questions about whether they contributed to Trump's victory over Clinton in 2016. We bring empirical evidence to this question, using ANES data to show that Democrats and Independents expressed unusual confidence in a decisive 2016 election outcome—and that the same measure of confidence is associated with lower reported turnout.

**Keywords:** impersonal influence, horserace, polling, forecasts[1]

[1]Supplementary materials are available in an online appendix. Replication data are on the JOP dataverse. Experimental protocols were reviewed by an IRB. No external funding supported this work.

> *"I don't know how we'll ever calculate how many people thought it was in the bag, because the percentages kept being thrown at people—'Oh, she has an 88 percent chance to win!"'* - Hillary Clinton quoted in Traister 2017

Political information about electoral competition is central to the study of political behavior. It can alter the strategic calculus used to decide whether or not to show up to the polls (e.g., Ansolabehere and Iyengar, 1994; Delli Carpini, 1984; Mutz, 1998)—after all, why should a voter take hours off work and arrange a trip to their polling place if they are certain one side will win or lose? Horserace coverage may play an outsized role in this calculus as it is widely available and dominates coverage of substantive issues in American elections (Iyengar, Norpoth, and Hahn, 2004; Patterson, 2016).

Yet, as we show, the dynamics between horserace coverage and voter behavior are shifting, because of a form of horserace coverage that has emerged in recent elections: the probabilistic forecast. In contrast to traditional horserace coverage that often focuses on unusual polls (Searles, Ginn, and Nickens, 2016) or speculates about a candidate's "paths to victory" (Silver, 2017) these forecasts aggregate polling data into a concise probability of winning, providing far more conclusive information about the state of a race.

In this paper, we show that probabilistic forecasts have fundamentally altered the political information environment, because they are 1) widely available in the media, 2) lead voters to different assessments of electoral competition and whether their vote matters (pivotality) compared to traditional vote share estimates, and 3) affect potential supporters of one political party more than another. We first show that probabilistic forecasts are highly salient in the mainstream media and provide evidence of their importance by documenting downstream effects on markets. We also show that they are more prominent in media outlets with left-leaning audiences. Using a survey experiment, we show that not only do these forecasts confuse some potential voters, they also lower perceptions that an election is competitive. Finally, we present an original behavioral game that simulates elections, which shows that probabilistic forecasts reduce voting as forecasts diverge from 50-50 odds, while vote share projections have no similar detectable effect.

## Pivotality and Electoral Behavior

Whether the horserace distracts voters from issues (Boudreau and McCubbins, 2010; Hardy and Jamieson, 2005; Iyengar, Norpoth, and Hahn, 2004; Patterson, 2005) or provides useful information about candidates (Bartels, 1988; Mutz, 1998), it undoubtedly provides information to voters about candidate's relative public support and the closeness of a race. Information about closeness can give voters a sense of whether their vote might matter, which ties into longstanding theories about why people vote. Work by Downs (1957) and Riker and Ordeshook (1968) on the calculus of voting points out that the strictly "rational voter" will not vote, because the actual odds of one person's vote being decisive in an election are near zero. The widely used formalization in Riker and Ordeshook (1968) follows: if $P$ is the (perceived) probability of casting the decisive vote, $B$ is the expected benefit of winning, $D$ is the utility of voting or sense of "civic duty," and C is the cost of voting, then one should vote if $P \times B + D > C$.

In addition to introducing the "civic duty" term, Riker and Ordeshook (1968) address this "rational voter paradox" by pointing out that people may *perceive* that their vote can influence the outcome of an election if it is close, despite long odds that they are actually pivotal. This conjecture is also consistent with the decision literature, which suggests that voters will tend to *over-estimate* the odds that they might cast the pivotal vote, because of the tendency to overweight the likelihood of salient but extremely rare events in decision-making (Tversky and Kahneman 1992; Barberis 2013; Fehr-Duda and Epper 2012)

Moreover, a potential voter's perception of the chances of casting a pivotal vote, $P$, depends on the information available to voters about the state of the race. We posit that if potential voters do not have conclusive information about who is expected to win a race, they should perceive meaningful uncertainty around $P$—their vote *could* matter. That means the payoff of voting, $P \times B$ in the model above, should be non-zero. Thus turnout should be (negatively) affected by more conclusive information about the state of a race.[2]

[2]This conjecture parallels Matsusaka (1995), which points out that the Riker and Ordeshook (1968)

Past work provides evidence that more conclusive information about the state of a race does indeed depress turnout. Some of the best evidence comes from work that analyzes the effects of releasing exit polling results before voting ends, which clearly removes uncertainty. Work examining the effects of East Coast television networks' "early calls" for one candidate or another on West Coast turnout generally find small but substantively meaningful effects, despite the fact that these calls occur late on election day (Delli Carpini, 1984; Sudman, 1986). Similar work exploiting voting reform as a natural experiment shows a full 12 percentage point decrease in turnout in the French overseas territories that voted after exit polls were released (Morton et al., 2015). These designs also isolate the effect of information about closeness from campaigns' tendencies to invest more in campaigns in competitive districts.

Other aggregate-level studies find similar patterns consistent with a relationship between uncertainty and turnout. First of all, a large body of literature has demonstrated robust correlations between tighter elections and higher turnout (see Geys, 2006; Cancela and Geys, 2016, for reviews). Furthermore, Nicholson and Miller (1997) provide evidence from statistical models that prior election returns also explain turnout above and beyond campaign spending, particularly when good polling data is unavailable. With ANES data we show that from 1952-2016, people who said that one candidate would "win by quite a bit" in pre-election polling were less likely to vote, even after conditioning on prior turnout, year, party, and actual electoral college and popular vote margin (see Table A2 and Figure A3).

Field experiments provide additional evidence of a causal effect of perceptions of electoral closeness on turnout. This literature finds substantive effects on turnout when polling results showing a closer race are delivered via telephone (among those who were reached, Biggers et al., 2017) but null results when relying on postcards to deliver closeness messages (for

model does not account for the *information* available to the potential voter. Rather, the expected benefit $B$ must be conditional on the voter's confidence in her expectations of the future consequences of policies that each candidate is likely to enact. This modification to earlier models better explains empirical patterns such as the association between higher turnout and phenomena related to better information about the $B$ term, such as education, aggregate campaign spending, and elite level issue-polarization.

which it's not possible to verify the treatment was actually read, Gerber et al., 2017; Biggers et al., 2017).[3] Finally, one study conducted in the weeks leading up to the 2012 presidential election found higher rates of self-reported, post-election turnout when delivering ostensible polling results *less* consistent with the extant polling data showing a comfortable Obama lead (Vannette and Westwood, N.d.).

How might probabilistic election forecasts affect perceptions of closeness and thus voting behavior? We hypothesize that by providing potential voters with conclusive information about who is expected to win a race, probabilistic forecasts may remove meaningful ambiguity around $P$, removing the perception that their vote *could* matter. We test this hypothesis in Study 1. We test the hypothesis that probabilistic forecasts remove the incentive to vote by removing uncertainty in Study 2. But first, we delve deeper into the reasons why probabilistic forecasts create certainty about what will happen in an election.

## The Probabilistic Horserace

While traditional horserace coverage provides the information potential voters use to gauge electoral competition, probabilistic election forecasts provide far more conclusive information about the state of a race. This means that probabilistic forecasts offer an opportunity for careful testing of some of the underlying dynamics explaining voter behavior—how flexible are perceptions of pivotality, and how does that map on to voter behavior.

These forecasts consist of complex meta-analyses that aggregate polls to reduce bias and other forms of error from one-off polling (Hillygus, 2011; Toff, 2017). The rigor that goes into these forecasts was underscored in 2008 when FiveThirtyEight successfully predicted nearly every state's Senate race and presidential result (Silver, 2008). What's more, when

[3]Emphasizing the closeness of an election in the context of canvassing has a large effect on turnout compared to no contact but is not necessarily stronger than other messages crafted to mobilize voters (Gerber and Green, 2000; Dale and Strauss, 2009; Enos and Fowler, 2014). However, these studies do not directly manipulate closeness.

news outlets cover traditional polls, they tend to focus on swings and unusual results (Searles, Ginn, and Nickens, 2016) and may provide speculative commentary about presidential candidates' potential "paths to victory," creating considerably more uncertainty compared with a conclusive, quantitative prediction from an election forecast (Silver, 2017).

Yet, the most powerful source of certitude may be the way these forecasts present their results to potential voters. Probabilistic forecasts present the probability of winning, $P(V_{share} > .5)$ among the top two candidates, instead of the expected vote share, $E(V_{share})$. Small differences in vote share estimates—the election metric most familiar to the public—generally correspond to very large differences in the probability of a candidate's chance of victory. And to map between $P(V_{share} > .5)$ and $E(V_{share})$ would require potential voters to perform a transformation such as: $P(V_{share} > .5) = 1 - \Phi\left(\frac{.5-\hat{\mu}_v}{\hat{\sigma}_v}\right)$, which means they need to have an estimate of the variance $\hat{\sigma}_v^2$ and a relatively sophisticated background in statistics.[4,5]

By combining the vote share and variance, probabilistic forecasts were designed to provide audiences with a better understanding of what the extant polling data tells us about a race. For example, consider a candidate who is projected to get 55% of the vote. The actual chance she will win is very different if the variance translates to a margin of error of +/- 1 compared with +/- 6. By converting the vote share and variance estimates into a probability, these forecasts are meant to help audiences better understand these two very different scenarios. But the result is numbers that are much higher (lower) than vote share estimates, and as we will show below, creates far more certainty about which candidate will win among the electorate.

This problem is compounded because it is so difficult to fully account for the variance, that is, to accurately estimate total survey error (TSE). In fact, work has found that TSE is

[4]Variance estimates are not usually provided, though the margin of error often is.

[5]Forecasters can also use non-parametric estimates based on simulation such as $\frac{1}{J}\sum_j^J I(\hat{\mu}_{v(j)} > .5)$ to estimate the probability of victory, which is particularly useful when for example 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 $\hat{\mu}_{v(j)}$.

often about twice as large as the estimates of sampling error provided in many polls (Shirani-Mehr et al., 2018). If the forecaster does not account for *total* survey error—including errors that may be correlated across surveys (Silver, 2014)—she will artificially inflate the estimated probability of a candidate's victory or defeat. [6] This phenomenon accounts for why so many forecasters in 2016 had Clinton's odds of victory above 90%. The Electoral College further complicates things as voters are actually dealing with the challenge of synthesizing a wide range of both state and national polling along with uncertainty about how state-level results might add up to electoral victory.

There are other reasons to expect that people will have difficulty reasoning about the probabilities that such forecasts present. With infrequent events like elections, people lack a reference point to understand probabilities in context, which induces erroneous behavior and thinking (Kunreuther, Novemsky, and Kahneman, 2001). For example, given our familiarity with weather forecasts, we likely wouldn't leave the house without an umbrella if forecasters projected a 35 percent chance of rain. However, elections are so rare and probabilistic forecasts so new that a 35 percent chance of victory lacks context.

People also tend to think in qualitative terms about the likelihood of specific events (Sunstein, 2002; Keren, 1991); if candidate A has an 85% chance of victory, they see victory the likely outcome (this may help explain why after the 2016 election, so many criticized forecasters for "getting it wrong," Lohr and Singer, 2017; Neyfakh, 2017)). But even more generally, one-off event probabilities—candidate A has an 85% chance of winning—are often misunderstood (Gigerenzer et al., 2007) compared to statements such as "if the election were repeated 1,000 times, candidate A would win 850 times; candidate B 150 times."

Furthermore, people sometimes conflate probabilistic forecasts with vote share projec-

[6] Although this will also result in underestimates of the margin of error that often accompany vote share projections, the point is largely moot—as we show below people tend to ignore these estimate (see supplementary materials). They may not be well-equipped to interpret margins of error regardless (Gigerenzer et al., 2007; Hoekstra et al., 2014)).

tions, and incorrectly conclude that Candidate A is projected to win 85% percent of the vote rather than to having an 85% chance of winning the election. We provide evidence for this in Study 1.

Finally, motivated reasoning may be more prevalent when people are interpreting probabilities versus interpreting vote share predictions. Because probabilities, by definition, convey uncertainty, people may bias their decisions in favor of a preferred outcome when interpreting this uncertainty (Piercey, 2009). For instance, whether a person interprets a 60 percent chance of Candidate A as particularly likely or not may depend on whether or not that person wants Candidate A to win or not.

## Empirical Context: The reach and potential consequences of forecasting

Recent years have seen the rising prominence of election forecasts, especially those that present their projections in terms of probabilities. However, news consumers do not need to visit forecasting websites like FiveThrityEight.com to be exposed to probabilistic forecasts. At least in the context of the 2016 presidential campaign, probabilistic forecasts were widely available in U.S. news outlets[7] and constituted an important part of the national conversation. In 2016, people mentioned forecasts dozens of times per day on cable news, visited websites offering forecasts at rates approaching major national media outlets, shared forecasts on social media at rates higher than major collections of polling data, and conducted millions of search queries to find these websites (Figure 1). The audience for probabilistic forecasts in the U.S. has not been distributed evenly across the political divide, leaning left. Table 1 shows that an index of the average ideology of users who share each

[7] For example, there were more than 9,800 articles published between from August 1 and November 7, 2016 that contained phrases indicating coverage of probablistic forecasting, according to Google News, see `https://goo.gl/qpP2wa`, accessed February 4, 2019.

Table 1: The U.S. social media audience for probabilistic forecasts leans left

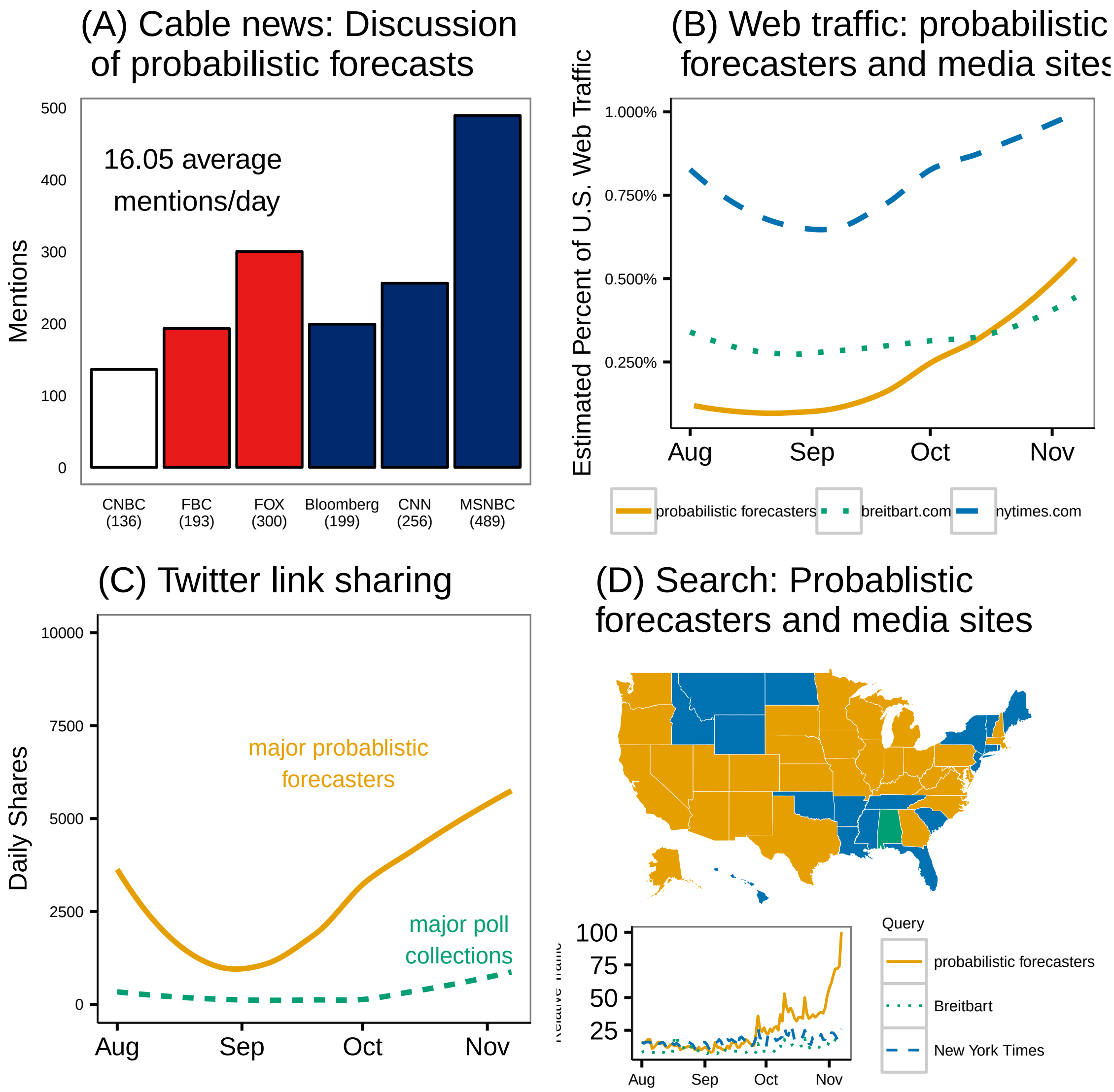
| Domain | Alignment |
|---|---|
| fivethirtyeight.com | -0.5225 |
| nytimes.com | -0.5469 |
| huffingtonpost.com | -0.6176 |
| realclearpolitics.com | 0.6616 |

domain, or ideological "alignment" (Bakshy, Messing, and Adamic, 2015)[8]. Every website hosting a probabilistic election forecast leans left. The only poll-aggregator with a conservative alignment score, realclearpolitics.com, does not display probabilistic forecasts. What's more, forecasts appear more often on channels with a more consistently liberal audience, as defined in (Mitchell et al., 2014; Bakshy, Messing, and Adamic, 2015).

While those on the left appeared more likely to see probabilistic forecasts in 2016, they also were more likely than independents or Republicans to believe that one candidate would "win by quite a bit" in ANES data (Figure 2). Indeed, more than 30 percent of Democratic respondents to the 2016 ANES expected Clinton to win by a comfortable margin, the highest proportion in the 2000s era of close electoral contests.

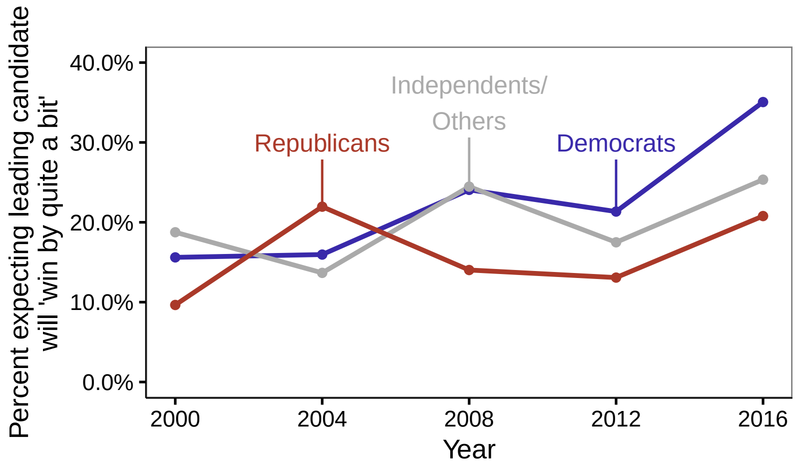
[8]Based on an index of the average ideology of users who share each domain, or ideological "alighnment" (Bakshy, Messing, and Adamic, 2015), every website hosting a probabilistic election forecast leans left. The only forecaster with a conservative alignment score, realclearpolitics.com, does not display probabilistic forecasts.

Figure 1: The reach of probabilistic forecasts in various media



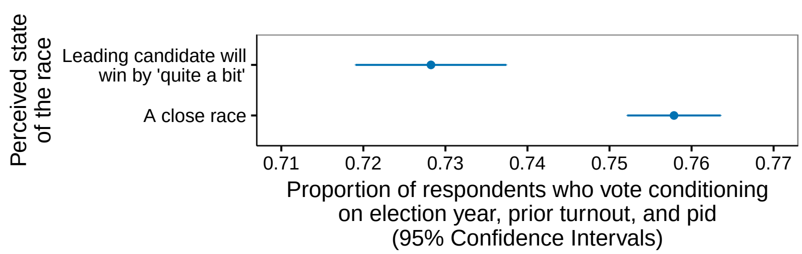

Note: (A) Cable news mentioned election probabilities about 16 times each day, and did so more frequently on channels with more consistently liberal audiences. (B) Forecasting websites had more web traffic than Breitbart.com and about 50% of the traffic to NYTimes.com the day before the election (estimated percent of total U.S. web traffic each day). (C) Individuals sent tweets with links to major probabilistic forecasts a total of 281,661 times and to major collections of polls 28,416 times (tweets per day shown in plot). (D) Individuals searched Google for election forecasting sites more than they searched for two major news outlets in most states, including where the vote was close—PA, WI, and MI (states are colored such that they correspond to the largest source of searches). On the day before the election, search query traffic for Breitbart.com and NYTimes.com was 25% of election forecasting sites. All data from 8/1/2016 to 11/7/16; details on the data analyses used here are in the supporting materials.

Figure 2: The partisan gap in expectations that the leading candidate would "win by quite a bit" was higher in 2016 than in other recent elections.



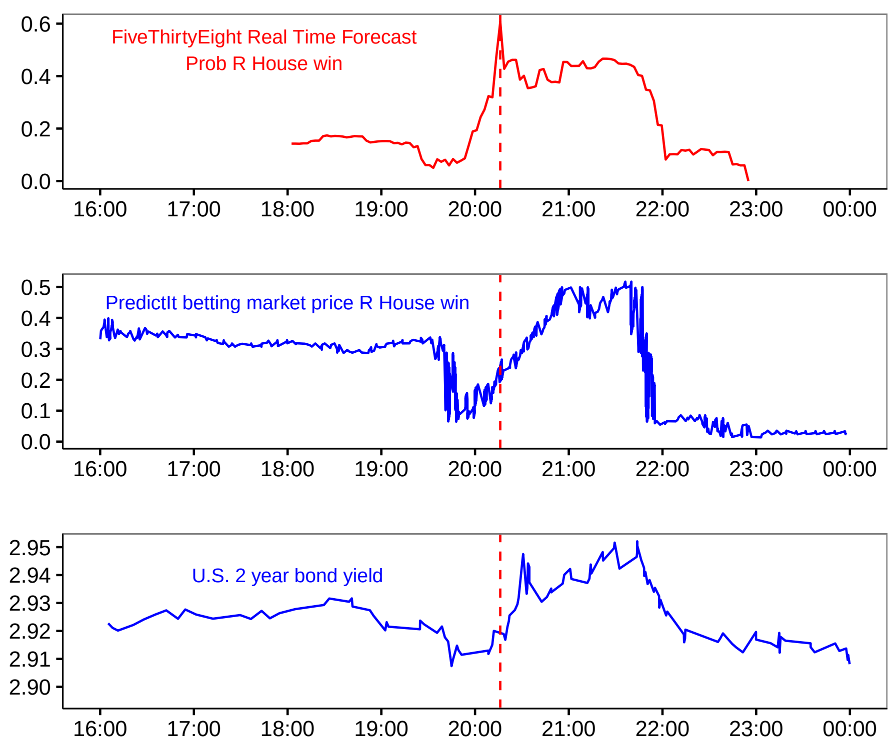

What's more, those who have stated that they expect one candidate to win by quite a bit are about two and a half percent less likely to vote than those who believe a race to be close (Figure 4).

Figure 3: Perceptions that one candidate will "win by quite a bit" are associated with lower turnout.




One remaining question is whether probabilistic forecasts may have fallen out of favor or lost their influence after what many perceive as their failure to forecast the 2016 election accurately. One way to interrogate this possibility is to revisit the question of whether probabilistic forecasts influence betting markets (raised in Tucker, 2012). We exploit a transitory error in FiveThirtyEight's real-time 2018 U.S. House forecast to shed light on all of these questions. On election night 2018, FiveThirtyEight's real-time forecast had GOP's odds of taking the House spiking at 60% at around 8:15PM (first reported in Smith and Greeley, 2018), because it was making biased inferences from partial vote counts (Silver, 2018). Shortly after, FiveThirtyEight changed its forecasting algorithm to wait for projections instead. However, during this period, the betting market PredictIt reported odds on a GOP victory moving above 50%. U.S. government bond yields also saw a brief spike of 2-4 basis points—which financial experts suggest was because markets expected to see more inflation under a Republican House (high spending, low taxes). These experts pointed out that this was unlikely to be mere noise because little else was happening in the U.S., and it was 1 am in the U.K. where the only market trading at the time was open (Smith and Greeley, 2018). These results suggest that probabilistic forecasts are still salient and influential, even after 2016.

Figure 4: After their real-time forecast had GOP's odds of taking the House spiking at 60% at around 8:15PM, PredictIt's odds on the GOP rose above 50-50, and U.S. government bond yields saw brief spike of 2-4 basis points.




In some ways, the widespread success and reliance on these forecasts represent a triumph of scientific communication. In addition to greater precision compared with one-off horserace polls, probabilistic forecasts can quantify how likely a given U.S. presidential candidate is to win using polling data and complex simulation, rather than leaving the task of making sense of state and national polls to speculative commentary about "paths to victory" (Silver, 2017). Furthermore, aggregating all polls reduces the ability of news outlets to focus on unusual polls that are more sensational or support a particular narrative (Searles, Ginn, and Nickens, 2016).

However, as we show below, these forecasts increase perceived certainty about election outcomes and can lower voter turnout. With a survey experiment, we show that (1) presenting win-probabilities increases the public's certainty that the leading candidate will win, compared to expected vote share; and (2) roughly 1 in 10 people confuse probabilistic forecasts with vote share estimates (but not vice-versa). Finally, we use a behavioral game to show that probabilistic estimates have substantively meaningful effects on voting above and beyond vote share estimates. The magnitude of the effects found here, the prevalence of probabilistic forecasts, and the small margins of recent presidential elections mean that these forecasts may have an impact on prominent elections.

## Study 1: The perceptual consequences of probabilistic forecasts

Our first study shows that, relative to horserace-style vote share estimates, presenting the probability a candidate will win simultaneously increases certainty about the ultimate victor and creates confusion. We rely on a dose-response experimental design and 4,151 respondents from wave 25 of Pew Research Center's American Trends Panel.

Our design relies on the fact that probabilistic forecasts present essentially the same information as vote share estimates with an accompanying margin of error in qualitatively different ways. In fact, *any* electoral projection based on one or more polls can be presented *in either form*. This is true regardless of how the underlying data are aggregated, weighted, modeled to account for correlated errors and combined with other economic or non-survey data.[9]

Participants in our study saw a hypothetical U.S. Senate race, where "Candidate A supports the majority of the policies you support and is well qualified for the job" (implying co-partisanship) and "Candidate B does not share your views and is less qualified than Candidate A." They then read a hypothetical projection based ostensibly on recently fielded surveys analyzed by "a prominent group of statisticians." The actual projection was randomly assigned to present Candidate A's average projected vote share — $E(V_{share})$, probability of winning — $P(V_{share} > .5)$, or both (see Table 2).[10]

Table 2: Allocation of respondents to qualitative treatment cells in Study 1

| | | 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 |

For ease of interpretation, we pooled across two additional factors—the presence of a margin of error (or not) and order.[11] Among conditions displaying the vote share, a margin of error of +/-2% was displayed to half of the 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

[9]Most major election forecasters in 2016 presented their projections both ways, but win-probabilities were generally more prominent than electoral college vote share estimates.

[10]The fact that this is a Senate race might prompt questions regarding whether survey error might be substantially higher than in a typical presidential race, such that a high win probability would map to a larger difference in vote share than what we present here. Yet there is little evidence that respondents considered 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.

[11]Results disaggregating these factors are consistent and are presented in Tables A7 and A8.

of error had no effect on judgments about the state of the race or certainty. Displaying the win-probability first resulted in slightly more extreme estimates of Candidate A's likelihood of victory and slightly more certainty about those judgments (See Table A8 in the Supplementary Information).

Estimates of Candidate A's vote share were randomly assigned to one of ten integer values between 45% and 55%. A plausible frequentist 95% CI of +/-2% was generated by simulating 20 surveys of 1000 people (see supplementary materials for details). Based on the same variance estimates, we also estimated the probability that Candidate A would get $>$ 50% of the vote and win the hypothetical election, which ranged from 13% to 87%.[12]

The numbers in Table **??** above rely on mapping the probability of victory to an estimate of the vote share accompanied by a 95% confidence interval, which in turn relies on the fact that both depend on the underlying distribution of a candidate's vote share. We estimated the expected vote share in our projection by the average of (hypothetical) survey sample means $\hat{\mu}_v = \frac{1}{N}\sum_i^N \bar{x}_i$ and the 95% confidence interval by $\hat{\mu}_v \pm T^{0.975}_{df=N} \times \frac{\hat{\sigma}_v}{\sqrt{N}}$, where $i$ indexes each survey and $N$ is the total number of surveys.[13] As is true of weighted, adjusted, and/or modeled estimate of $\hat{\mu}_v$ and $\hat{\sigma}_v$, the probability of victory, or $P(\mu_v > .5)$ can then be estimated by $1-\Phi\left(\frac{.5-\hat{\mu}_v}{\hat{\sigma}_v}\right)$. 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 when for example 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 $\hat{\mu}_{v(j)}$.

Respondents judged (1) how *certain* they were that candidate A would win or lose on a

[12] We use parameters typical of real-world surveys; under certain unusual conditions that result in dramatically higher variance—for example, less than five responses per survey—win-probability numbers can be smaller than vote share estimates.

[13] We do not need to employ complex modeling strategies that adjust for correlated errors or population covariates here, because we are drawing simulated data directly from a known and fully specified hypothetical population.

5-point scale, which we transform so all values fall between 0 and 1, (2) the *share* of the vote they expected candidate A to receive, and (3) how *likely* they thought candidate A was to win (both on a 0-100 point scale).

Presenting aggregated survey estimates as a probability created the impression that a candidate will win more decisively (Figure 5). After seeing our vignette, respondents reported being on average 7% more certain in their judgments about who would win after we presented the probability of victory ("likely to win" condition) compared with the vote share estimate ("vote-share", $\beta = 0.07$, $T = 7.0$, $P = 3.7 \times 10^{-12}$, see also Table A6). This effect was substantially stronger when the candidate was ahead in the polls, as shown in Figure 5.

Respondents also reported significantly more extreme judgments of vote share when they saw win-probabilities compared with vote-share in our vignette ($\beta = 1.49$, $T = 8.92$, $P < 2 \times 10^{-16}$, see also Table A6). For example, when presented with vote share estimates that Candidate A would win 55% of the vote, participants expected candidate A to get 56.5% of the vote (95% CI: 55.3%, 57.6%). When presented with the commensurate 87% probability that Candidate A would win, participants expected Candidate A to get 64.6% of the vote (95% CI 63.0%, 66.2%)—an eight percentage point difference.

When estimating the likelihood of victory, respondents reported estimates far closer to 50-50 than the information provided in the vignette, across all conditions. This was particularly true for projections further away from a neck-and-neck race. Even when presented with a forecast putting Candidate A's chance of victory at 87%, the average participant said the likelihood of A's victory was 69.9% (95% CI 67.9%, 71.9%)–a 17 percentage point difference. When presented with commensurate vote share estimates that put Candidate A's share of the vote at 55%, respondents were more than 27 percentage points off—the average participant reported a 59.6% likelihood that Candidate A would win (95% CI 58.1%, 61.0%).

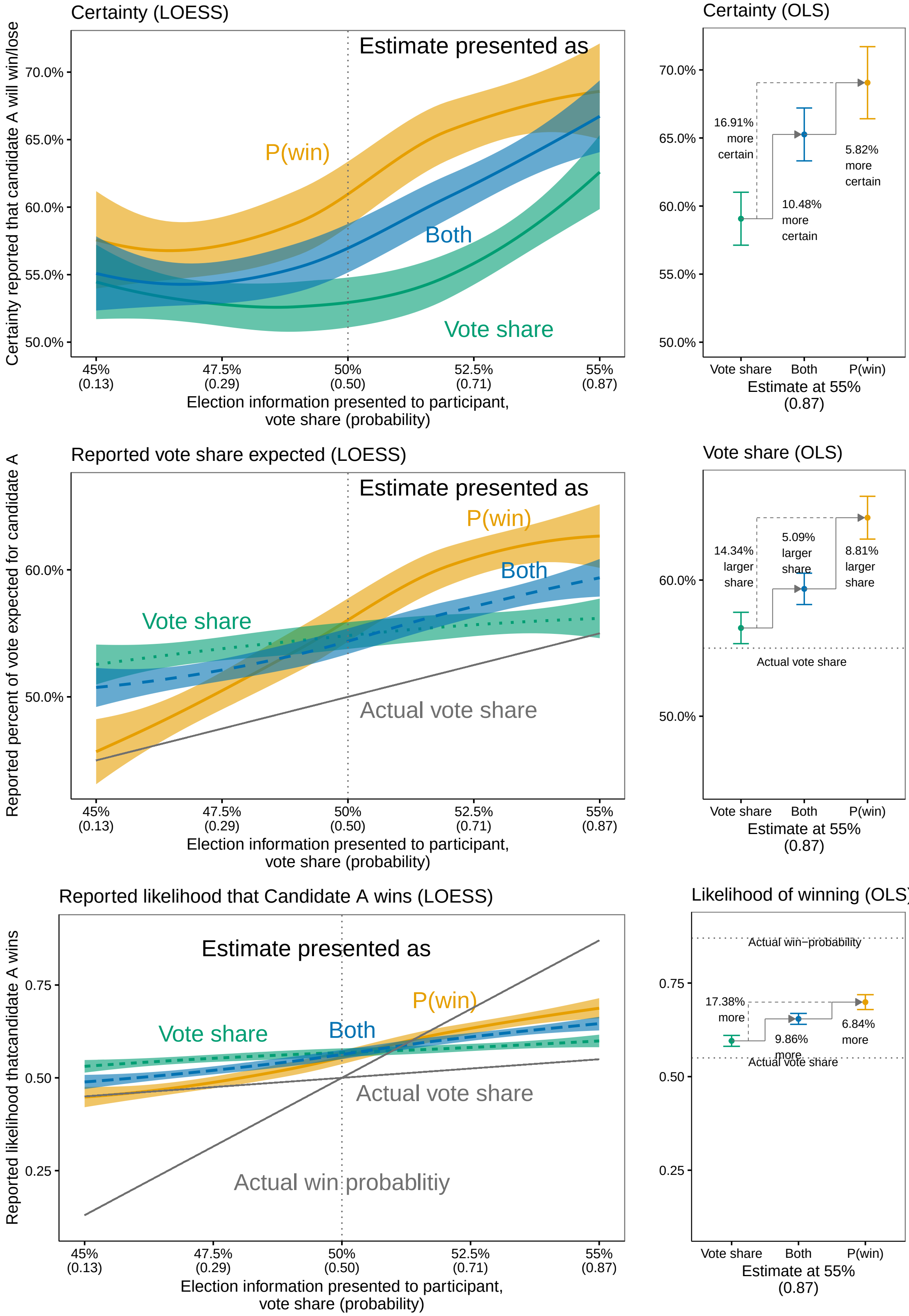



Figure 5: Effects of probabilistic forecasts on perceptions of an election

Probabilistic forecasts create the impression that the leading candidate will win more decisively, with higher certainty in judgments about which candidate will win, particularly for the leading candidate (top panel) and more extreme judgments of anticipated vote share (bottom panel), even when accompanied by vote share projections (the "both" condition). Participants are less accurate when attempting to judge the likelihood of winning (middle) than vote share (top). Plots on the right show differences when vote share is fixed at 55% (.87 probability). Lines fit using LOESS in plots on the left; results based on OLS regression in plots on the right, 95% confidence bands/intervals shown.

It is not surprising that respondents who saw vote share more accurately reported the vote share and that respondents who saw probabilities more accurately reported probabilities– we would be concerned that respondents were not paying attention if this were not the case. The more interesting comparison involves the reported vote share among those who saw probabilities: when faced with a high probability of winning, respondents reported vote share as if they expected a blowout. Yet in the condition that provided vote share, likelihood hovered around 50-50. In fact, the total error in estimating the likelihood of winning is huge, compared with the error in reporting vote share, irrespective of condition. And the error is in the direction of 50-50 odds.

This raises the question of why respondents shrank their estimates of the odds of victory so aggressively toward 50-50. In an ideal world where respondents have a deep knowledge of statistics, we would expect them to shrink estimates toward 50-50, because most forecasters underestimate total survey error (Shirani-Mehr et al., 2018) and hence forecasting error, *providing odds that are too far from 50-50.* Likewise, because many things can happen from the time a forecaster analyzes polling results until election day, it might make sense to further shrink estimates toward 50-50. And even if we assume most respondents lack this sophistication, respondents may still have good reason to shrink what they reported toward 50-50, based on broad coverage of forecasters' inflated estimates of a Clinton victory in 2016, irrespective of whether they understand that this was in large part due to their failure to properly account for total error.

Another potential factor, which is supported by evidence, is that some respondents did not seem to process the distinction between vote share and likelihood of victory. Indeed, 38% of participants reported the same number for vote share and likelihood of victory.[14] Respondents were significantly less likely to make this mistake in the "both" condition, in

[14]Removing these respondents does not substantively alter the results. Because this is measured post-treatment and varies by condition, it could be problematic to present an analysis of the data without these respondents included.

which they saw distinct vote share and win probability estimates, $M_{Both} = 0.34$, $M_{others} = 0.40$, $T(3570.6) = 4.29$, $P < 2 \times 10^{-5}$.[15] What's more, when participants reported the same numbers, they tended to provide assessments of the win-likelihood that were *closer to the vote share* than the probability of winning provided in the experiment. In fact, even in the full sample, the average distance between reported likelihood and provided vote share is lower than the average distance between reported likelihood and provided win likelihood, *even in the win-likelihood condition*, as shown in Figure 6.

It seems unlikely that explanations involving respondents simply having difficulty translating between probabilistic forecasts and vote shares can fully explain the shrinkage toward 50-50 we see for respondents' win probability estimates. If that were the case, those in the "both" condition would be expected to do equally well compared with those in the win-probability condition. Yet, those in the "both" condition engage in *more* aggressive shrinkage, resulting in lower accuracy than respondents who only see win probability.

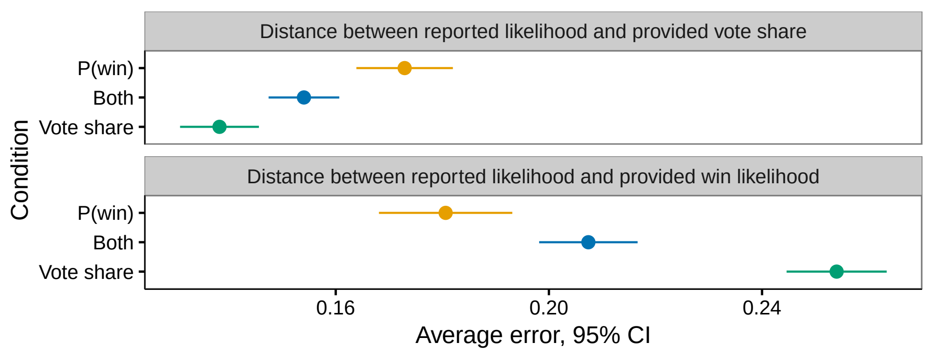



Figure 6: Average distance between respondents' assessments of the "likelihood of victory" and (1) vote share provided in the experiment (above); (2) win-probability provided in the experiment (below), by condition.

This raises the question of how many respondents simply reported the vote share from the experiment as the likelihood and vice versa. This was much more likely when respondents saw win-probabilities. In the win-probability-only condition, 8.6% of respondents estimated

[15] These relationships also hold when removing respondents who reported 50% for both their assessment of the vote share and their assessment of the likelihood of victory. 17% of respondents did this.

*vote share* to be within 1% of the win-probability provided. In the condition that provided both win-probabilities and vote share projections, 2.1% of respondents estimated vote share to be within 1% of the provided win-probability. In the vote share only condition wherein no win-probability number was provided, 0.6% of respondents estimated vote share to be within 1% of the equivalent win-probability number (See Table A7 for more detail).[16] The evidence suggests that a substantial proportion of people have trouble distinguishing between vote share and probabilities and that for many, the "default" mode of thinking is in terms of vote share, rather than in terms of the likelihood a candidate wins.

Finally, we turn to self-reported intent to vote. Around 93% of respondents reported the intent to hypothetically vote in all conditions. After conditioning on past voting history and party, we observed preliminary evidence that participants were slightly less likely to say they would hypothetically vote when seeing more extreme probabilistic forecasts (Table A9), though this finding should be considered exploratory.

Of course, it is significantly less effort to report the intent to vote in a survey than to expend the effort required to get to the polls on a Tuesday in the face of potential long lines and competing work/family obligations. Indeed, other work has found null results when examining the effect of closeness on self-reported intent to vote (Ansolabehere and Iyengar, 1994). Study 2 below attempts to better capture the economic trade-offs entailed in voting, and shows that when voting presents a non-trivial cost, people do in fact vote at lower rates after viewing probabilistic forecasts that suggest that a win or loss is very likely.

### Robustness

One concern with Study 1 is that we used candidates for the U.S. Senate. It is possible that participants knew that state-level polling is nosier and less credible than the national polling

[16]Using an .8 cutoff produces the following numbers: 8.6% in probability of winning condition, 1.9% in the both condition, and 0.6% in the vote share condition. Using a 1.2% cutoff produces the following numbers: 10.3% in probability of winning condition, 3.3% in the both condition, and 1.5% in the vote share condition.

used in presidential forecasts. We conducted a replication study that varied the candidate office (U.S. House/U.S. Senate/U.S. President) and found no differences between offices. We used a sample from Mechanical Turk ($N = 275$) and a simplified design using two of the ten numerical values for probability/vote share (45% and 55%). We found no detectable differences in responses by the office sought by the hypothetical candidates (see Table A11).

Figure 5 also shows a bias in evaluating candidates that shared respondents' views, consistent with a tendency toward motivated reasoning when interpreting polling results Babad and Katz (1991); Dolan and Holbrook (2001). This motivated reasoning effect attenuates significantly when presenting the win-probability and asking for evaluations of candidate B, who *doesn't* share the participant's views. In a replication of Study 1 (data from Qualtrics Panel, N=178) 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 (we randomly drew these values above and below even odds). When the other candidate was reported to be ahead, respondents were less certain of victory ($\beta = -0.19$, $T = -2.661$, $P < 0.009$), reported a smaller expected vote share ($\beta = -13.20$, $T = -2.249$, $P = 0.03$), and a lower probability of victory ($\beta = -15.22$, $T = -2.30.0$, $P = 0.02$).

## Study 2: How probabilistic forecasts affect behavior

In what follows, we show that when faced with the costs and benefits of voting in a behavioral game, more extreme probability estimates decrease voting. However, changes in projected vote share estimates have no detectable average effect on behavior. Our data come from 1,171 respondents (5,845 trials) drawn from a national online non-probability survey panel recruited by Qualtrics Panels.

Participants were instructed that they would ostensibly engage in a game with other participants who were completing the survey. Prior to the game, participants read instructions, reviewed examples and completed comprehension questions. Before each of five rounds, participants were randomly assigned to either Team A or Team B. At the start of the game (see Figure 7) they were given \$15. They were told that voting for their team (\$1 cost), increased the chance that their team would win. If their team won [lost], they would earn [lose] \$2. In our setup, \$1 is the cost to "vote." Before starting a round, we presented participants with a pre-vote poll, where we asked about vote intention. Participants were told this would be used along with the responses of other players and information from prior games to calculate the chance that their team would win (following the model for many forecasters). Participants were then shown the results ostensibly calculated from this poll, which included the two-team electoral vote share, randomly assigned to 40-60, and the probability that each team would win, randomly assigned to between 1-50 if a team's vote share was $< 50$, and 50-90 if the vote share was $\geq 50$.

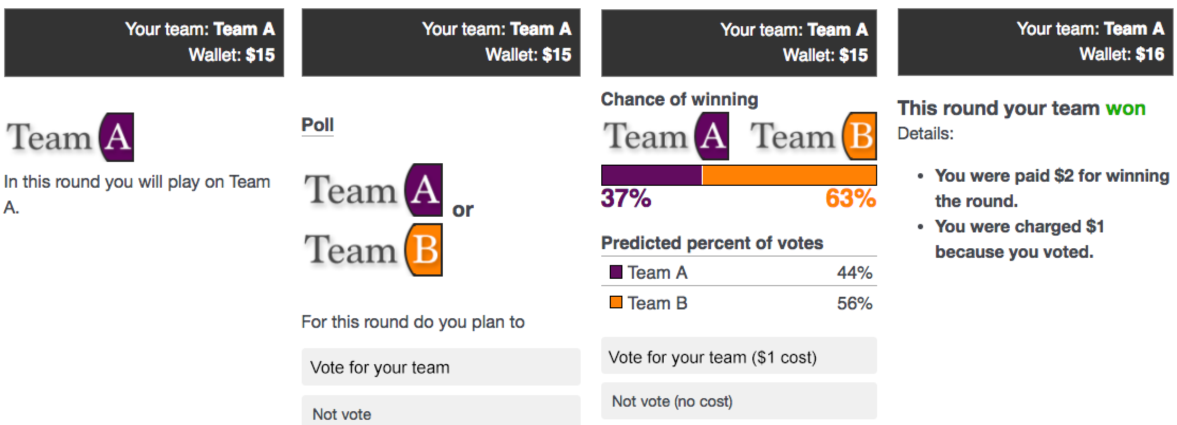



Figure 7: Study 2 stimuli and prompts

Note: Following team assignment, participants took a poll about their intentions in the current round. After the system "processed" the poll, the projections were shown to participants and they were asked to decide if they wanted to actually vote for their team or abstain (bottom,left). Finally results were displayed (bottom right).

Game stages (stages 2-6 repeated in each of the five rounds):

1. Instructions, examples, and comprehension questions
2. Random assignment to Team A or Team B
3. Respondents polled on their voting intentions in the round
4. Presentation of vote share and probability of victory

5. Decision to vote (\$1 cost) or not vote (no cost)
6. Feedback (\$2 cost if the participant's team lost; \$2 award if participant's the team won)

As the probability of winning diverged from 50-50, participants were less likely to vote ($\beta = -0.17$, $T = -4.1$, $P = 4.2 \times 10^{-5}$, see Figure 8).[17] However, we detected *no* effect of vote share extremity on voting ($\beta = -0.13$, $T = -0.7$, $P = 0.48$). Comparing the standardized effects of probability and vote share likewise reveals that probability has a much larger effect (see Table A18).[18]

Given the cost of voting and payoffs, people will maximize their winnings if they only vote if $\$4 * P(decisive\_vote) > \$1$, or $P(decisive\_vote) > 0.25$, which corresponds to an extremely narrow band around even odds, and shrinks as the perceived number of players in the game increases ($N$). Figure 8 clearly shows that people do not strictly maximize their winnings based on this calculus, but behave in a way more consistent with a qualitative assessment of whether their vote might matter.

[17]Data were analyzed using a multi-level model with random intercepts for each user because of repeated observations; p-values estimated based on Satterthwaite approximations to degrees of freedom. We found no evidence of directional differences, see Table A16.

[18]We also tested the hypothesis that these standardized betas were equivalent using a likelihood ratio test, as implemented in the R function "car::linearHypothesis" (Fox and Weisberg, 2011). We can safely reject this null hypothesis, residual $DF_{restricted} = 5552.8, DF_{full} = 5551.8, F = 5.67, P < 0.02$.

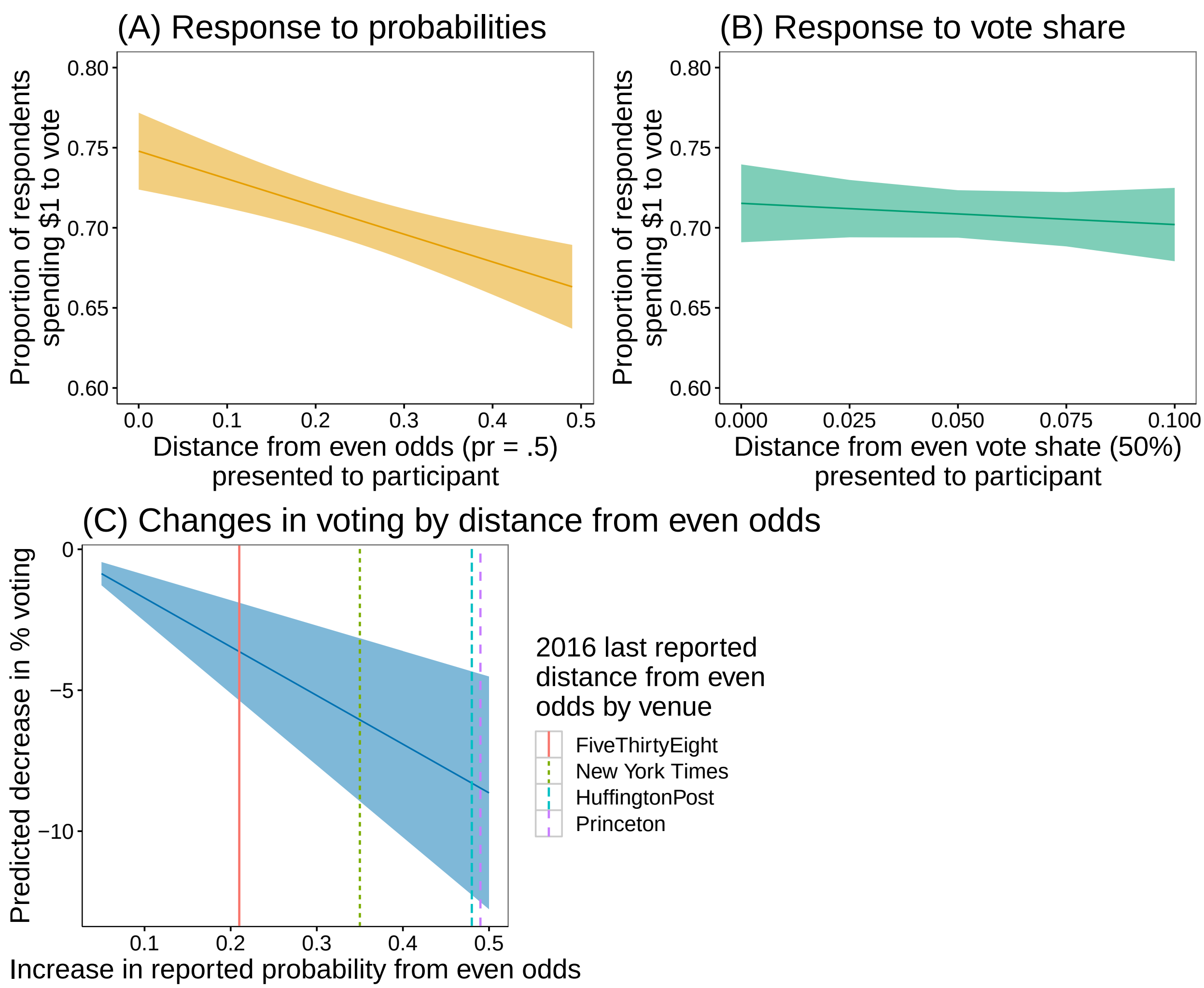



Figure 8: Effects of probabilistic forecasts on voting behavior

Note: When presented with both the probability of victory and vote share, participants are less likely to vote as the probability their team will win increases (A), but do not change behavior in response to differences in reported vote share (B). Changes in probabilities from even odds are compared with the final predicted Clinton advantage from various aggregators (C). Lines are marginal effects with 95% confidence bands.

For context, consider that 2016 forecasts reported win probabilities between 70% and 99%, giving Clinton an advantage ranging from 20% to 49% beyond 50-50 odds. Clinton ultimately lost by 0.7% in Pennsylvania, 0.2% in Michigan, 0.8% in Wisconsin, and 1.2% in Florida. To the extent that this experiment generalizes to real-world elections, the effects above are large enough to meaningfully alter turnout in marginal states—an increase of 20% over even odds in this study lowered voting by 3.4% (95% CI: [1.8%, 5.1%]) and an advantage of 40% lowered the voting by 6.9% (95% CI: [3.6%, 10.2%]). If as the evidence provided above suggests, Democrats were more affected by probabilistic forecasts in 2016, probabilistic forecasts may have a strong enough effect on turnout to constitute an important factor influencing the election.

**Robustness**

These results are not conditional on a participants' understanding of probabilities. Following the game, participants completed The Berlin Numeracy Test (Cokely et al., 2012), which presents respondents with a series of questions about probabilities in applied situations. We found no significant main effect of numeracy and no interaction between numeracy and forecasted probabilities displayed in the game (see table A19).

Furthermore, our results also do not depend on people confusing vote share with probabilities or incorrectly recalling either value. After each voting round, we asked respondents to report back to us the vote share and probability we supplied for the round. Of those respondents who gave a valid response, 161 respondents reported incorrect probabilities only once, while 36 made the mistake more than once. Removing respondents who made such a mistake does not substantively impact our results (Table A15). This stands in contrast to study 1, in which respondents tended to shrink the likelihood estimates they reported toward 50-50. However, in study 2 we directly incentivized attention to the race with money, which should be expected to reduce reporting "50-50" responses. And unlike study 1, there was immediate feedback on the "election," which may have enabled participants to become more familiar with the metric. Finally, it may be that in Study 1, respondents reported different results because they do not equate probability and likelihood, and in Study 2 we asked about the *probability* rather than the *likelihood*.

Some people might have 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 A16 shows that there were no significant interactions between round and absolute distance between vote share and probabilistic forecast, suggesting that on average this did not affect our results.

Another question is whether respondents simply dismissed vote share as a noisy signal because unlike win-probability, it contains no information about precision. However, the polling data were presented as a census. And even if some respondents thought it was a sample or thought about other sources of error, such an effect would be inconsistent with the null effects of displaying measures of precision in Study 1. This presentation is also consistent with multiple probabilistic forecasting websites that present the probability of winning and vote share estimates without a margin of error.

One way Study 2 differs from a real-world election is that the number of voters is much smaller, which means that a person's vote is more likely to be pivotal. Players in Study 2 were not directly told how many other people were playing, which may have created ambiguity. We explore this issue an in additional robustness test for Study 2 where we explicitly manipulated group size ($N$) as reported to participants in a repeated measures design, to gauge whether it attenuated the negative effect of probabilistic forecasts on turnout. We use 238 participants (1,190 trials) drawn from the Qualtrics Panel. We test this question with an interaction term between the probabilistic forecast and the group size.

Prior to the game, participants were told: "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 do not find an effect of group $N$ on behavior (Table A20) 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.

This suggests that people do not calculate pivotality in a manner consistent with a strict interpretation of rational choice theory. These data are more consistent with a model of the world (and much prior work Riker and Ordeshook, 1968; Keren, 1991; Sunstein, 2002) in which people have a qualitative notion of whether they might plausibly impact the vote—when the probability of a candidate's victory seems rather low or rather high, they appear less likely to vote.[19]

Finally, the order of probabilities and vote share was fixed in Study 2 (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 this last replication study, we randomly varied the order of the information (at the participant-level). We detected no effect of order on behavior (see Table A20).

# Conclusion

We show that probabilistic horserace coverage lowers perceived electoral competition, confuses many potential voters, and, as odds diverge from 50-50, can have demobilizing effects compared coverage focusing on vote share. Using a survey experiment, we show that presenting forecasted win-probabilities decreases the impression that an election is competitive compared to vote-share projections (Study 1). Furthermore, these forecasts confuse many—more than a third of people estimate a candidate's likelihood of winning to be identical to

[19]However, pivotality would certainly be larger and easier to compute in smaller groups. To address this, we replicate this robustness test on Mechanical Turk with 662 participants using groups ranging in size between 4 and 21 and report the results in Table A22 in the appendix. Even when group sizes are very small we find no evidence that respondents are computing pivotality. Instead, the participants are simply relying on the reported probability when deciding if they should vote. We recover a main effect of probabilities ($\beta = -0.34$, $T = -2.85$, $P = 0.02$) consistent with all our replications. Predicted vote share is not significant ($\beta = 0.37$, $T = 0.55$, $P = 0.37$). Most importantly, group size is never substantively large or statistically significant.

her vote share, and on average people estimate that likelihood to be closer to the vote share than the probability of winning after they see both types of projections. Perhaps most importantly, higher win probabilities, but not vote share estimates, decrease voting in the face of the trade-offs embedded in our economic game (Study 2). Taken together, results suggest that forecasting can fundamentally alter the information environment available to potential voters, with the potential to change the outcome of elections.

The media visibility of probabilistic forecasts means their effects may not be limited to turnout—there may be additional downstream effects. Election coverage has secondary effects on donations and mobilization (Mutz, 1998), and political cynicism (Cappella and Jamieson, 1997). Furthermore, candidates' perceptions of the closeness of an election can affect campaigning and representation (Enos and Hersh, 2015; Mutz, 1997). These perceptions can also shape policy decisions—for example, prior to the 2016 election, the Obama administration's confidence in a Clinton victory was reportedly a factor in the muted response to Russian intervention in the election (Miller, Nakashima, and Entous, 2017). Around the same time, FBI Director James Comey said he felt that it was his duty to write a letter to Congress saying he was reopening the investigation into candidate Hillary Clinton's emails because he was certain she would win (Keneally, 2018).

This work has other limitations worth noting. First, these findings do not speak to the data underlying probabilistic forecasting, the statistical modeling underpinning projections, or the ultimate accuracy of probabilistic forecasts. Instead, they speak only to how people interpret these forecasts and behave based on those interpretations.

Second, Study 1 presents a hypothetical election scenario, which provides a high degree of experimental control but lacks additional contextual information (Grimmer, Westwood, and Messing, 2014)—for example, media narratives about each candidate/campaign—that can translate to smaller real-world effects. On the other hand, there are reasons to expect that the effects we observe may actually be conservative—the stronger salience of party identity combined with motivated reasoning during an actual election may produce considerably larger effects on confidence when a potential voter's candidate is ahead. Of course, a candidates' strongest supporters may be both particularly likely to confide in their candidate's likelihood of victory as they reject evidence to the contrary but also particularly likely to vote no matter what.

Third, the economic game presented in Study 2 tests the behavioral consequences of the economic trade-offs related to voting, but is not measuring actual voting in an actual election. Furthermore, participants may have had a heightened perception about the potential pivotality of their vote compared to a real-world election due to the smaller pool of voters. However, in an additional experiment, we explicitly manipulated group size as reported to participants, which did not attenuate the effects. While this experimental paradigm offers a high degree of control and opportunities to investigate mechanisms such as those explored in 5 follow-on studies offered in the appendix, field experimental replications would lend higher ecological validity to these findings.

Although we show that the public have difficulties understanding and correctly responding to probabilistic forecasts, they are a relatively new addition to modern elections. It is possible that the public will gain competency over time as exposure grows. We, however, are skeptical. Despite the problems with the 2016 forecast, voters are still likely to rely on probabilistic information (even Democrats who might have strong reasons to mistrust such forecasts). In general humans—even outside the context of elections(e.g., Gigerenzer and Edwards, 2003; Gigerenzer et al., 2005)—consistently demonstrate such profound ineptness with probabilities that even a massive effort to educate the public on how to interpret election probabilities is likely to have little effect. The problem, we think, is not deficits in education or irresponsible media narratives, but simply that probabilities are inherently intuitive.

While forecasts are only one among many factors in play during an election, our work suggests that they can affect perceptions and ultimately outcomes, particularly in light of their media visibility in 2016. Given the far stronger effects for probabilistic forecasts compared with vote share projections, those concerned about the effects of polling–from depressing turnout (Mutz, 1998; Morton et al., 2015) to other political calculations (Enos and Hersh, 2015)–should be especially attentive to probabilistic forecasts.

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