Revisiting the Link between Expected Election Outcomes and Turnout

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Abstract. Westwood et al. (2020) causally demonstrate that probabilistic forecasts reduce beliefs about electoral competition, which, in turn, results in a lower propensity to vote. They argue this may have cost Hillary Clinton votes among overconfident supporters. Using the American National Election Study (ANES) from 2004 to 2016, we find that believing an election will not be close *can* affect turnout. The strongest evidence, however, suggests only those who believe their party's candidate will *lose* by quite a bit are less likely to vote. Analysis of validated vote in 2016 does not support the conclusion that probabilistic forecasts cost Hillary Clinton votes among overconfident Democrats. The results suggest, if the probabilistic forecasts had any effect, they either lowered turnout among Republicans confident their candidate will lose or stimulated turnout among Democrats confident their candidate will win.

Voting for president is arguably democracy's most basic form of political participation. Yet, if people rationally considered the costs and benefits of voting—where the costs (*C*) are always non-zero and the benefits include the expected benefit of your candidate winning the election (*B*) multiplied by the probability of casting a decisive vote (*P*)—no one would turn out to vote (Downs 1957). However, people's subjective estimate of *P* is often much higher than an objective calculation would suggest (Riker and Ordeshook 1968). That is, when considering why people vote, we should not assume people enter in the *true* calculus of the probability of them casting the decisive vote—a number that is essentially zero—we should take into account their *perception* that they will be pivotal—a number that could vary based on information they are receiving about the election.

As an individual's perception of electoral competition increases, his or her perceived probability of being pivotal should also increase. This should mean turnout will be higher when elections are expected to be close (Grofman et al. 1998). How do voters come to believe an election will be close? While news media have an incentive to present polling information that suggests elections are close (Searles et al. 2016), organizations have been producing probabilistic forecasts (e.g., Nate Silver's 538 model) in recent years. These forecasts aggregate polls and, combined with historical data, produce the probability of a candidate winning election. In 2016 especially, these forecasts received a great deal of attention.

Westwood et al. (2020) demonstrate with two experiments that this form of probabilistic forecasting causes increased certainty about the election, thus making people think their vote will not matter and decreasing their probability of turning out to vote. This result is almost certainly true. They also use the American National Election Study (ANES) to demonstrate that people who believe one presidential candidate will win by "quite a bit" are less likely to turn out. However, their analyses do not directly consider heterogeneous treatment effects. In this note, we address the question of *who* would be less likely to vote because of probabilistic forecasts (or news in general) that suggests a particular candidate is more likely to win.

Westwood et al. (2020) infer an answer based on (1) their finding that the audience for these probabilistic forecasts leans left and (2) the probabilistic forecasts calling the Democratic presidential nominee, Hillary Clinton, the clear favorite. Westwood et al. (2020) write, "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" (11).

This is where we diverge from Westwood et al. (2020). The forecasts themselves shape the news coverage surrounding the candidates, which all engaged voters see—not just those on the left. News coverage shapes perceptions about the likely outcome of the election among this segment of the public—this was true before the forecasts existed. And most importantly, if beliefs about election outcomes have an effect on turnout decisions, they should have different effects for those who believe they will be on the winning side and those who believe they will be on the losing side.

This argument is based on the idea that people are not simply instrumental voters, but also *expressive* voters (Fiorina 1976; Bruter and Harrison 2017). Voters who think they will be on the losing side may indeed be demobilized, and not just because they believe they are less likely to be pivotal. Voters may use news coverage stating a candidate is likely to lose as a cue about the quality of a candidate. In this case, we would imagine the information would act like a negative ad, demobilizing supporters of the candidate (Krupnikov 2011).

Voters who think they will win, however, may turn out based on the belief that other party supporters are voting (Großer and Schram 2006), or even "jump on the bandwagon" for a possible winner (Marsh 1985). Hence, enthusiasm of being a likely winner may offset the negative effect of not believing you're pivotal, leading to no net effect of probabilistic forecasts on turnout for likely winners—or even potentially a positive effect if the forecasts create enough enthusiasm.

Data

We use the American Election Studies (ANES) from 2004 to 2016. This includes an election, 2004, that predates Nate Silver's model. The main difference in our analysis from Westwood et al. (2020) is the coding of the key independent variable: expected outcome. They use a dummy variable that distinguishes whether the respondent said the election would be close or one candidate would win by quite a bit. They show that individuals who say the election will not be close are 2.5 percentage points less likely to vote in a pooled analysis using data from 1952-2016.

Our independent variable is trichotomous: the respondent believes (1) the election will be close; (2) his or her party's candidate will *win* by quite a bit; or (3) his or her party's candidate will *lose* by quite a bit. In Table 1, we present the distribution of this variable separately for Democrats and Republicans by year. The table shows that most people say the election will be close every year and that partisans do not typically say their party's candidate will lose by quite a bit. However, we see 8% of Democrats in 2004, 10% of Republicans in 2008, and 9% of Republicans in 2016 predict a large loss for their party. As Westwood et al. (2020) note, no set of partisans were more confident of victory than Democrats in 2016.

The key dependent variable in our main analysis is self-reported turnout. It is widely believed that the self-reported measure of turnout is subject to issues of social desirability. When we examine the 2016 election specifically, we replicate the analysis with validated vote (which *also* has potential errors, see Berent, Krosnick, and Lupia 2016). The ANES provides a probability that the validated vote is correct. We included only individuals for whom the probability was greater than 0.99 (coded

1 as having voted) and individuals for whom the probably was less than 0.01 (coded 0 as having not voted). In SI-C, we rerun the model lowering the thresholds to .95 and .05 as a robustness check.

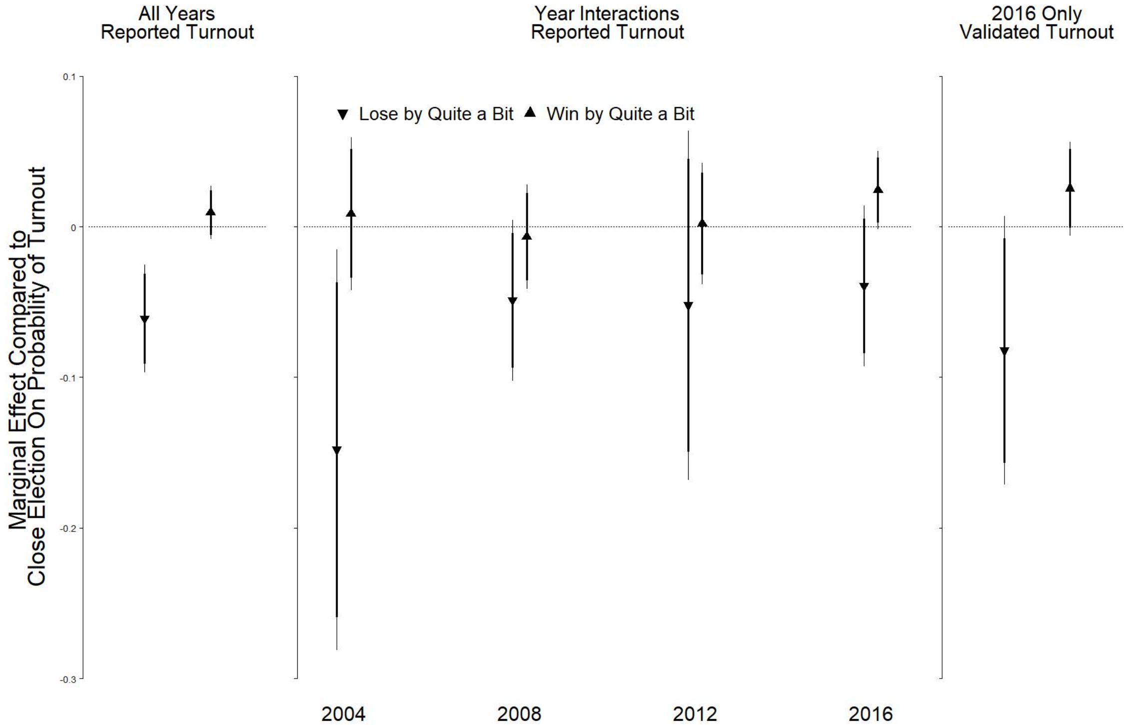
We also include a series of control variables that previous research suggests are important for turnout, including basic demographics, political awareness, interest in politics, how long the respondent has lived in the community, and whether they turned out in the previous election as a proxy for whether they are a habitual voter (see e.g., Highton 1997, Plutzer 2002).[1] We also include whether the state was determined to be a "Battleground State" pre-election, as individuals who live in a battleground state are more likely to be engaged with the election (Settle et al. 2016). The coding of all variables is available in SI-A.

Table 1. Distribution of Expected Outcome in Each Year by Party

	Democrats				Republicans			
	2004	2008	2012	2016	2004	2008	2012	2016
Win By Quite a Bit	8.2%	26.2%	20.0%	33.1%	22.4%	7.0%	12.8%	11.2%
Lose By Quite a Bit	8.2%	2.3%	0.6%	2.3%	0.7%	10.7%	4.1%	9.3%
Will Be Close	83.7%	71.6%	79.4%	64.6%	77.0%	82.3%	83.1%	79.5%
N	540	1239	3016	1866	456	589	1926	1635

[1] We attempt to use the same coding in all years. This is not possible with political awareness because the standard ANES questions in which respondents identify various political office holders are not included in 2008. Thus, here we use interviewer estimates of respondent levels of knowledge, a measure highly correlated with actual knowledge, though there are some biases (Ryan 2011).

Figure 1. The effect of expected outcome on turnout.



Results from logit models. Full models are available in SI-B and SI-C. Thin bars indicate 95% confidence intervals; thick bars indicate 90% confidence intervals.

Results

In the first two panels of Figure 1, we present the marginal effect of perceived expected election outcome from two logit models (the full models are available in SI-C). In the figure, triangles facing downward display the effect of believing your party's candidate will lose by quite a bit compared to believing the election will be close and triangles facing upward display the effect of believing your party's candidate will win by quite a bit compared to believing the election will be close. Both models pool all years, but the second model includes an interaction between expected outcome and dummy variables for each election year. We note, however, the AIC is lower in the model *without* the interaction effects, suggesting it is superior (Berry, DeMeritt, and Esarey 2010).

The first pair of triangles display the results of the pooled model (without the interactions). Believing your party's candidate will lose the election by quite a bit is associated with a six percentage-point decrease in the probability of voting ($p<.001$; all reported p-values are one-tailed). There is no statistically significant difference between believing your party's candidate will win the election by quite a bit and believing the election will be close.

The next four pairs of triangles present the marginal effects for each year. We see a negative effect of believing your party's candidate will lose by quite a bit in 2004 ($p=.015$) and 2008 ($p=.037$), with 2004 having the largest point estimate for the effect—about 10 points larger than any other year. For 2012 and 2016, the effects are negative and the sizes are similar to 2008, but the confidence intervals overlap with 0. Further, the confidence intervals of the effect for all years overlap, suggesting we cannot distinguish the size of these effects across the years.

Believing your party's candidate will win by quite a bit has no statistically significant effect for any year, with the exception of 2016. In that year, we see a *positive* effect of 2.4 percentage-points ($p=.031$). This would imply that the probabilistic forecasts *encouraged* turnout among Democrats wgi believed they would be on the winning end if they had any effect at all.

In the final panel of Figure 1, we look just at 2016—the year that probabilistic forecasts received the most attention—and use validated turnout (full model is in SI-C). Here we indeed see a statistically significant negative effect for believing your party's candidate will lose ($p=.035$), while the positive effect of believing your party's candidate will win falls short of conventional significance ($p=.054$). These results would suggest that the most likely effect of probabilistic forecasts in 2016 was reduced turnout among those who believed their candidate would lose—i.e., Republicans.

This leads us to conclude that coverage stating Clinton was likely to win did not cost her the election. We can think of two obvious objections to our analysis to this point. First, some people who believe their candidate will win by quite a bit are not bold enough to say that in a survey.

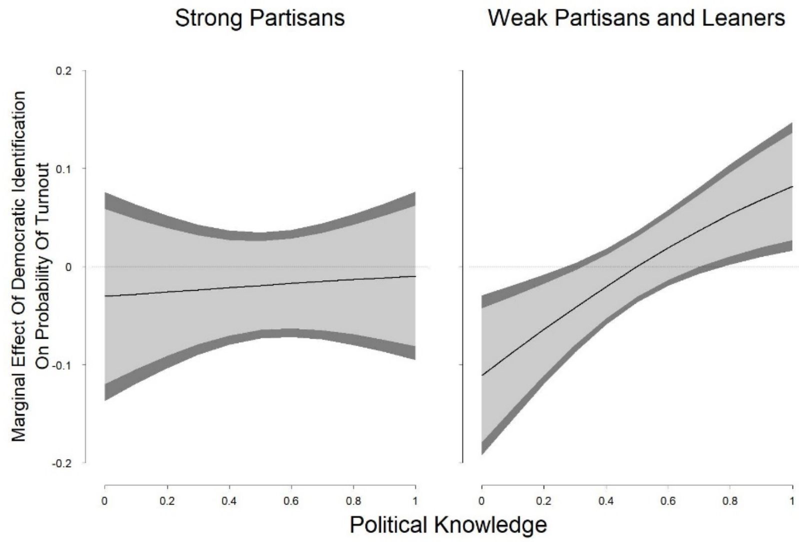
Second, not looking for differential effects by strength of partisanship may dilute the effect, as strong partisans are likely to turnout no matter what.

As an alternative analysis, then, we examine political awareness as a moderating variable between partisanship and turnout. Individuals who are more politically aware should be most affected by the probabilistic forecasts—either through direct knowledge of the forecast or via news coverage informed by them.[2] Hence, if the coverage of probabilistic forecasts hurt Clinton, we would be most likely to see lower turnout among weak Democrats who are politically aware.

Results from a logit model that tests this possibility are in Figure 2. The full model is in SI-D, along with an alternative specification with previous turnout instead of partisan strength that leads to the same substantive conclusion. As we would predict, we see similar turnout levels for Democrats and Republicans among strong partisans at all levels of political awareness. Among weak and leaning partisans, Democrats are less likely to turn out to vote when they are less politically aware (p=.004)—this is the group less likely to be affected by news coverage. Among the most politically aware, Democrats were *more* likely to turn out (p=.007). This is consistent with either aware Republicans being demobilized due to reading their party's candidate will lose or aware Democrats being mobilized due to reading their party's candidate will win—or perhaps a small amount of both.

[2] Importantly, we find that political awareness and believing one's party's candidate will win by quite a bit are positive correlated among Democrats and negatively correlated among Republicans in 2016 (see SI-E).

Figure 2. Checking for differential turnout rates between Democrats and Republicans at different levels of political awareness.



Results from logit model. Full model is available in SI-D. Darker shading indicates 95% confidence intervals; lighter shading indicates 90% confidence intervals.

Conclusion

Westwood et al. (2020) causally demonstrate that probabilistic horse-race coverage causes lower perceived electoral competition—which, they argue, should result in lower turnout. They open with a quote from Hillary Clinton: "I don't know how we'll ever calculate how many people thought it was in the bag," implying that Clinton may have lost in key battleground states because her voters were overconfident. The results in this paper are consistent with the idea that news coverage in 2016—which included probabilistic forecasts—lead individuals to believe Clinton "had it in the bag." The results are *not* consistent, however, with the notion that this hurt Clinton electorally.

Using data from presidential elections from 2004 to 2016, we find that believing the election will not be close may be associated with lower turnout, but the evidence suggests this occurs among individuals who believe their party's candidate will be on the losing side. When we look at 2016 specifically, we find that politically aware weak and leaning Democrats were *more* likely to vote—a finding incompatible with the notion that probabilistic forecasts cost Clinton the election by lowering turnout among overconfident Democrats. This evidence is more consistent with the idea that weak and leaning Democrats jumped on the bandwagon because they thought they would win.

Overall, however, the most robust results suggest a null effect of believing your party's candidate will win by quite a bit on turnout. Of course, we lack the statistical power to demonstrate that this is a true null. Effects of interventions on turnout are often small, making it difficult to find an effect. The elections in the 2016 battlegrounds were quite close and any small effect *could* have made a difference—hence, overconfidence could have cost Clinton the election but it would have been a null effect in our models. Thus, we ran one more model to check if the news coverage predicting a Clinton win demobilized her voters in key states (see SI-D). In this model, looking just at validated votes in 2016 among Democrats in battleground states, we do *not* find a null effect—instead, Democrats in these states who believed the election was unlikely to be close were eight percentage points *more* likely to turn out (p=.018).

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Supplemental Information for

Revisiting the Link between Expected Election Outcomes and Turnout

A. Coding of all variables.

B. Models for pooled ANES data (2004-2016) with reported turnout.

C. Models for 2016 ANES data with validated turnout.

D. Additional models for 2016 ANES data with validated turnout.

E. Models with the respondent's expected outcome as the dependent variable.

SI-A. Coding of all variables.

This table lists the variables used to measure all variables. Variable coding on next page.

Variable	2004	2008	2012	2016
Expected Outcome	V043093 V043094	V083073 V083074	preswin_win preswin_close	V161146 V161147
Age	V043249a	V081104	dem_age_r_x	V161267x
Woman	V041109a	V081101	profile_gender	V161342
White	V043299	V083251a	dem_racecps_white	V161310x
Black	V043299	V083251a	dem_racecps_black	V161310x
Hispanic	V043299	V083251a	dem_hisp	V161310x
Education	V043254	V083218x	dem_edu	V161270
Income	V043293x	V083248x	inc_incgroup_pre	V161361x
Lived in Community	V043308	V083266a	dem3_yearscomm	V161331a
Political Awareness	V045162 V045163 V045164 V045165	V083303	ofcrec_speaker_correct ofcrec_vp_correct ofcrec_pmuk_correct ofcrec_cj_correct	V162072 V162073a V162074a V162075a V162076a
Democrat	V043116	V083098x	pid_x	V161158x
Strong Partisan	V043116	V083098x	pid_x	V161158x
Caniddate Difference	V043038 V043039	V083037a V083037b	ft_dpc ft_rcp	V161086 V161087
Political Interest	V043001	V083001a V083001b	interest_following	V161004
Ideological Extremity	V043085	V083069	libcpre_self	V162171
Previous Turnout	V043002	V083007	interest_voted2008	V161005
Battleground State	V041201a	V081201a	sample_state	V161010e
Turnout	V045018x	V085036x	postvote_rvote	V162032x
Validated Turnout	NA	NA	NA	vote2016_prob

Expected Outcome

Two dummy variables: respondent's believes his or her party's candidate will lose by quite a bit and respondent's believes his or her party's candidate will win by quite a bit with respondent's believes the election will be close.

Age

0=18-29; 0.2=30-39; 0.4=40-49; 0.6=50-59; 0.8=60-69; 1=70 or older

Woman

0=Man; 1=Woman

White

0=non-white; 1=white

Black

0=non-black; 1=black

Hispanic

0=not Hispanic; 1=Hispanic

Education

0=No High School; 0.25=High School; 0.50=Associates or Some College; 0.75=Undergraduate Degree; 1=Graduate Degree

Income

0=1st Quintile; 0.25=2nd Quintile; 0.5=3rd Quintile; 0.75=4th Quintile; 1=5th Quintile.

Lived in Community

Three dummy variables: 3-5 years, 6-9 years, 10 or more years with 2 or fewer years as the reference group

Political Awareness

(2004) Proportion of officer holders correctly identified: Speaker of the House, Vice-President, UK Prime Minister, Chief Justice of US

(2008) Interviewer assessment of the respondent's level of knowledge 0=Very low; 0.25=Fairly low; 0.50=Average; 0.75=Fairly high; 1=Very high

(2012) Proportion of officer holders correctly identified: Speaker of the House, Vice-President, UK Prime Minister, Chief Justice of US

(2016) Proportion of officer holders correctly identified: Speaker of the House, Vice-President, German Chancellor, Russian President, Chief Justice of US

Democrat

0=Republican; 1=Democrat

Strong Partisan

0= Leaning Partisan, or Weak Partisan; 1=Strong Partisan

Candidate Difference

The natural log of the difference between the feeling thermometer rating of the presidential candidate from the respondent's party and the feeling thermometer rating of the other party's presidential candidate. If the respondent rates the other party's candidate as higher, the score is changed to 0. We add one to the score prior to taking the natural log.

Political Interest

(2004, 2012, 2016, and some randomly assigned in 2008)

0=not much interested; 0.5=somewhat interested; 1=very much interested

(everyone else in 2008) 0=not interested at all; 0.25=slightly interested; 0.50=moderately interested; 0.75=Very interested; 1=Extremely Interested

Ideological Extremity

0=moderate; 0.33333=Slightly Liberal /Conservative; 0.66667= Liberal /Conservative; 1=Extremely Liberal /Conservative

Previous Turnout

0=did not vote in previous presidential year election; 1=voted in previous presidential year election

Battleground State

A dummy variable for the respondent's state; it is coded 1 if the media reports found for that year name the state as a battleground state and 0 otherwise.

(2004 – from the *New York Times*) Colorado, Florida, Iowa, Minnesota, New Hampshire, New Jersey, New Mexico, Oregon, and Pennsylvania

(2008 – from the *Washington Post*) Colorado, Florida, Indiana, Missouri, Nevada, New Hampshire, North Carolina, Ohio, Pennsylvania, and Virginia

(2012 – from Milita and Ryan 2019) Colorado, Florida, Iowa, Nevada, New Hampshire, North Carolina, Ohio, Virginia, and Wisconsin

(2016 – from *Politico*) Colorado, Florida, Iowa, Michigan, Nevada, New Hampshire, North Carolina, Ohio, Pennsylvania, Virginia, and Wisconsin

SI-B. Models for pooled ANES data (2004-2016) with reported turnout.

Models used for first two panels in Figure 1.

	Coef.	Z-Value	Coef.	Z-Value
Lose By Quite a Bit	-0.474	-3.610	-1.235	-2.72
Win By Quite a Bit	0.084	1.060	0.100	0.34
Year: 2008	-0.170	-1.060	-0.190	-1.14
Year: 2012	-0.884	-6.560	-0.923	-6.01
Year: 2016	-0.321	-2.110	-0.409	-2.75
Lose X 2008			0.791	1.49
Lose X 2012			0.871	1.72
Lose X 2016			0.901	1.82
Win X 2008			-0.163	-0.47
Win X 2012			-0.083	-0.25
Win X 2016			0.135	0.44
Age	0.094	0.800	0.098	0.83
Woman	0.267	4.340	0.268	4.35
White	0.414	3.160	0.418	3.18
Black	0.679	5.180	0.689	5.24
Hispanic	0.245	1.920	0.243	1.91
Education	0.700	3.510	0.697	3.47
Income	0.539	5.510	0.538	5.50
In Community 3-5 Years	0.356	3.930	0.356	3.89
In Community 6-9 Years	0.341	2.520	0.340	2.46
In Community 10 or more	0.431	3.250	0.431	3.18
Political Awareness	0.815	6.590	0.821	6.65
Democrat	-0.027	-0.320	-0.018	-0.22
Strong Partisan	0.238	4.120	0.239	4.10
Candidate Difference (Logged)	0.135	3.590	0.137	3.63
Political Interest	0.689	6.310	0.687	6.25
Ideological Extremity	0.165	1.540	0.165	1.51
Previous Turnout	1.813	21.730	1.810	21.95
Battleground State	-0.118	-0.930	-0.117	-0.92
Constant	-2.302	-7.870	-2.271	-7.34
A.I.C.	6001.03		6007.9	
N	7873		7873	

Logit models. Standard errors clustered on respondent's home state.

SI-C. Models for 2016 ANES data with validated turnout.

First model is used in the third panel in Figure 1. Second model tests robustness of the validated vote threshold.

	.01/.99 Validated Vote		.05/.95 Validated Vote	
	Coef.	Z-Value	Coef.	Z-Value
Lose By Quite a Bit	-0.474	-1.92	-0.451	-1.83
Win By Quite a Bit	0.162	1.57	0.154	1.50
Age	0.650	4.39	0.672	4.55
Woman	0.189	1.42	0.162	1.26
White	-0.090	-0.35	-0.088	-0.35
Black	-0.285	-1.09	-0.227	-0.87
Hispanic	-0.187	-0.77	-0.151	-0.63
Education	0.604	3.31	0.583	3.32
Income	0.745	5.14	0.689	4.91
In Community 3-5 Years	0.537	4.12	0.500	3.84
In Community 6-9 Years	0.570	3.26	0.521	2.99
In Community 10 or more	0.888	6.27	0.814	6.15
Political Awareness	0.729	3.44	0.764	3.87
Democrat	-0.018	-0.17	-0.036	-0.34
Strong Partisan	0.183	1.48	0.184	1.64
Candidate Difference (Logged)	0.074	1.68	0.059	1.33
Political Interest	0.281	2.01	0.284	2.26
Ideological Extremity	0.222	1.43	0.247	1.64
Previous Turnout	1.188	8.68	1.149	9.08
Battleground State	0.283	2.17	0.222	1.77
Constant	-2.728	-6.72	-2.571	-6.91
A.I.C.	2643.3		2719.4	
N	2638		2686	

Logit models. Standard errors clustered on respondent's home state.

SI-D. Additional models for 2016 ANES data with validated turnout.

Second model is used in Figure 2. The first model is used to demonstrate that the model with the interactions is a better fitting model than the one without interactions.

	Coef.	Z-Value	Coef.	Z-Value
Political Awareness	0.811	4.03	0.492	1.83
Democrat	0.020	0.19	-0.551	-2.62
Strong Partisan	0.187	1.51	0.330	1.12
Awareness X Democrat			1.099	2.85
Awareness X Strong Partisan			-0.068	-0.13
Democrat X Strong Partisan			0.381	1.01
Awareness X Dem. X Strong			-0.992	-1.52
Age	0.675	4.66	0.690	4.70
Woman	0.211	1.62	0.225	1.69
White	0.051	0.22	0.033	0.14
Black	-0.164	-0.66	-0.150	-0.59
Hispanic	-0.039	-0.16	-0.045	-0.19
Education	0.549	3.02	0.540	2.98
Income	0.712	4.92	0.719	4.93
In Community 3-5 Years	0.561	4.42	0.554	4.34
In Community 6-9 Years	0.463	2.93	0.477	2.90
In Community 10 or more	0.850	6.11	0.858	6.04
Candidate Difference (Logged)	0.062	1.44	0.056	1.29
Political Interest	0.287	2.14	0.294	2.13
Ideological Extremity	0.211	1.46	0.212	1.44
Previous Turnout	1.151	9.36	1.162	9.12
Battleground State	0.252	1.93	0.259	1.94
Constant	-2.805	-7.62	-2.646	-6.78
A.I.C.	2786.6		2784.2	
N	2749		2749	

Logit models. Standard errors clustered on respondent's home state.

This model is the Democrats only model discussed at the end of the conclusions.

	Coef.	Z-Value
Quite a Bit	-0.043	-0.32
Battleground State	0.047	0.25
Quite a Bit X Battleground	0.581	1.92
Age	0.784	3.53
Woman	0.131	0.79
White	-0.266	-0.75
Black	-0.314	-0.96
Hispanic	-0.169	-0.5
Education	0.625	2.14
Income	0.785	3.41
In Community 3-5 Years	0.460	2.13
In Community 6-9 Years	0.385	1.66
In Community 10 or more	0.644	4.07
Political Awareness	1.078	3.81
Strong Partisan	0.122	0.81
Candidate Difference (Logged)	0.081	1.11
Political Interest	0.199	1.01
Ideological Extremity	0.179	0.79
Previous Turnout	1.079	6.01
Constant	-2.532	-4.95
A.I.C.	1515.7	
N	1453	

Logit models. Standard errors clustered on respondent's home state.

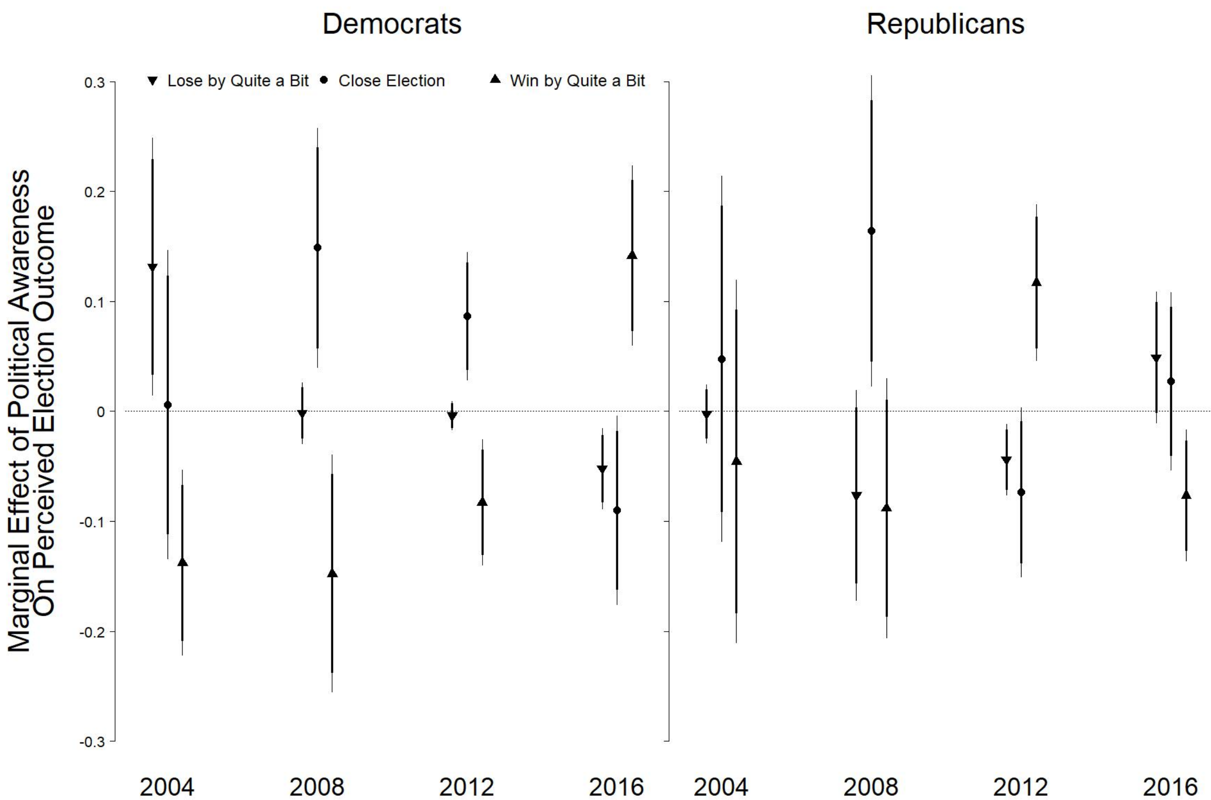
SI-E. Models with the respondent's expected outcome as the dependent variable.

The goal of this analysis is to understand which respondents believe their party's candidate will win or lose by quite a bit in each election year. If the probabilistic election forecasts are having an effect, then we would expect that politically aware Democrats will become more confident in later years when the forecasts predicted a convincing Democratic win—especially in 2016. The forecasts predicted a Democratic win every year, but, as Westwood et al. (2020) argue, they were most confident and heavily publicized in 2016. Hence, we interact *Political Awareness* and the year of the election.

The results of the full models – we run separate models for Democrats and Republicans -- are available at the end of this section. In the figure below, we present the marginal effect of *Political Awareness* for each year separately for Republicans and Democrats. The Democratic results confirm the argument in Westwood et al. (2020). Prior to 2016, more knowledgeable Democrats were less likely to believe that their party's candidate will win by quite a bit – even though, Democrats won two out of three of those elections. In 2016, however, as the models were predicting a high likelihood of a Democratic victory, more knowledgeable Democrats were more likely to believe their party's candidate would win by quite a bit.

On the Republican side, we see no clear pattern. *Political Awareness* was unrelated to beliefs about the expected outcome of the election in 2004, associated with belief in a close election in 2008, and correlated with the belief in an easy Republican win in 2012. In the key year of 2016, however, we do see that politically knowledgeable Republicans were more likely to believe their party's candidate would lose by quite a bit.

We should note that the strongest predictor of expected outcome in the election is difference in the feeling thermometer ratings between the presidential candidate from the respondent's party and the other party's candidate. When respondents believe their party's candidate is clearly superior, they are more likely to believe the candidate will win by quite a bit. When they are uncertain which candidate they prefer, they are more likely to believe their party's candidate will lose by quite a bit.



Democrats

	Lose By Quite a Bit		Win By Quite a Bit	
	Coef.	Z-Value	Coef.	Z-Value
Political Awareness	1.801	2.43	-1.966	-2.7
Year 2008	-0.201	-0.32	1.007	2.81
Year 2012	-1.348	-1.98	0.169	0.51
Year 2016	0.861	1.74	0.473	1.42
Awareness X 2008	-2.089	-1.99	1.156	1.49
Awareness X 2012	-2.574	-1.83	1.297	1.71
Awareness X 2016	-3.815	-4.02	2.598	3.48
Age	-0.347	-1.01	-0.230	-1.92
Woman	-0.174	-0.79	-0.312	-4.17
White	0.305	0.71	-0.093	-0.72
Black	-0.049	-0.1	0.337	2.3
Hispanic	0.092	0.2	0.424	3.2
Education	-0.905	-1.89	-0.500	-3.27
Income	-0.929	-2.56	-0.105	-0.88
Strong Partisan	-0.356	-1.32	0.272	3.33
Candidate Difference (Logged)	-0.184	-2.4	0.396	7.38
Political Interest	-1.169	-3.4	-0.130	-1.02
Ideological Extremity	0.380	1.06	0.262	2.2
Constant	-1.126	-1.82	-2.714	-7.13
A.I.C.	5402.4			
N	4630			

Multinomial logit model.

Republicans

	Lose By Quite a Bit		Win By Quite a Bit	
	Coef.	Z-Value	Coef.	Z-Value
Political Awareness	-0.453	-0.18	-0.288	-0.54
Year 2008	3.194	2.14	-0.463	-0.79
Year 2012	2.085	1.4	-1.252	-3.3
Year 2016	2.345	1.6	-0.548	-1.41
Awareness X 2008	-0.589	-0.23	-0.934	-1.08
Awareness X 2012	-1.408	-0.54	1.232	2.1
Awareness X 2016	0.954	0.38	-0.545	-0.9
Age	-0.160	-0.66	0.129	0.73
Woman	0.065	0.44	-0.093	-0.85
White	-0.361	-1.31	-0.579	-2.8
Black	0.884	2.07	-0.143	-0.34
Hispanic	0.328	1.05	0.079	0.35
Education	0.403	1.32	-0.522	-2.36
Income	0.036	0.15	-0.454	-2.66
Strong Partisan	-0.413	-2.27	0.103	0.87
Candidate Difference (Logged)	-0.191	-3.41	0.477	5.14
Political Interest	-0.163	-0.66	0.767	3.82
Ideological Extremity	-0.370	-1.41	0.470	2.46
Constant	-3.649	-2.45	-2.750	-5.5
A.I.C.		3833.9		
N		3438		

Multinomial logit model.