P&P Politics & Policy

Citizen Forecasts of the 2008 U.S. Presidential Election

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We analyze individual probabilistic predictions of state outcomes in the 2008 U.S. presidential election. Employing an original survey of more than 19,000 respondents, we find that partisans gave higher probabilities to their favored candidates, but this bias was reduced by education, numerical sophistication, and the level of Obama support in their home states. In aggregate, we show that individual biases balance out, and the group's predictions were highly accurate, outperforming both Intrade (a prediction market) and fivethirtyeight.com *(a poll-based forecast). The implication is that electoral forecasters can often do better asking individuals who they think will win rather than who they want to win.*

Keywords: Citizen Forecasts, Individual Election Predictions, 2008 U.S. Presidential Election, Partisan Bias, Voter Information, Voter Preference, Wishful Thinking Bias in Elections.

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Politics & Policy, Volume 40, No. 6 (2012): 1019-1052. 10.1111/j.1747-1346.2012.00394.x
Published by Wiley Periodicals, Inc.

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Analizamos las predicciones probabilísticas individuales de los resultados estatales para la elección presidencial de los Estados Unidos en 2008. Usando una encuesta original de más de 19,000 participantes, encontramos que los partidistas dieron una mayor probabilidad a su candidato preferido, pero este sesgo se vio reducido por factores como la educación, sofisticación numérica, y el nivel de soporte hacia Obama en sus estados de origen. En conjunto, mostramos que los sesgos individuales se compensan y que las predicciones grupales fueron de gran precisión, superando a Intrade *(un mercado de predicciones) y* fivethirtyeight.com *(un pronóstico basado en encuestas). La implicación es que los pronosticos electorales pueden ser mejorados al preguntar a los individuos quién piensan que ganará en lugar de preguntar quién quieren que gane.*

How do individuals form expectations about future political events? Are predictions influenced by desires? Do social surroundings play a role? Guided by these questions, this study analyzes individual forecasts of state outcomes in the 2008 U.S. presidential election. In line with previous work, we confirm a strong impact of preferences on expectations, known as "wishful thinking" (WT) bias. Thus Republicans gave higher probabilities to McCain victories and Democrats to Obama victories. At first, the presence of this bias seems to question the epistemic value of citizen forecasts. However, we find two reasons to be more optimistic. First, we identify several factors that reduce WT bias, including individual sophistication and social surroundings. Second, we show that individual biases balance out in aggregate, making the group as a whole highly accurate.

Although several studies have investigated electoral prediction, we draw on an original online survey of more than 19,000 respondents, with unprecedented variation over time and location. The survey includes respondents from all 50 states (as well as outside the United States) and covers every day in the two months prior to the election. Further, we asked respondents their predicted probabilities of Senators Barack Obama or John McCain winning various states, rather than who they predicted would win nationally, providing us with richer data than in most existing research.

Building on past work, we show that WT bias is reduced by education and an original measure of numerical sophistication. In addition, we provide the first evidence that an individual's residence matters—respondents whose home states gave a larger vote share to Obama had smaller WT bias and higher accuracy. We explain this by appeal to the informational role of one's surroundings and social networks. The effect is robust to controlling for other state characteristics, including campaign spending. We also investigate how patterns of individual prediction change over time as new information is acquired. We find that predictive accuracy improved as election day approached, but this was almost entirely concentrated among the most sophisticated individuals. Republicans also failed to improve their accuracy until the election was very near, indicating an initial resistance to accept Obama's approaching victory.

Guided by an interest in party evaluation and the dynamics of political deliberation, there exists a robust literature in political science on how preferences relate to the formulation of factual beliefs (Bartels 2002; Gerber and Huber 2010; Mendelberg 2002; Nickerson 1998; Oswald and Grosjean 2004), information sharing (Meirowitz 2007), and the evaluation of arguments (Kunda 1990; Taber, Cann, and Kucsova 2009). However, with the exception of work on electoral prediction, there remains a lacuna on how expectations form about political events. This is an unfortunate oversight, as political scientists have several reasons to care about individual predictions of elections and other events. Businesses and stock markets adjust their behavior based on anticipations of future election winners (Snowberg, Wolfers, and Zitzewitz 2007). The expected closeness of races influences campaign spending decisions (Erikson and Palfrey 2000) and voter turnout (Blais 2000). Moreover, expectations can powerfully shape the disappointment or satisfaction individuals experience from electoral outcomes (Classen and Dunn 2010; Gerber and Huber 2010; Krizan, Miller, and Johar 2010; Wilson, Meyers, and Gilbert 2003).

Last, there exists a small cottage industry in political forecasting for its own sake. We compare the accuracy of our survey group's forecasts with a prediction market (Intrade) and aggregated polling data (from http://www.fivethirtyeight.com, hereafter 538) and find that the properly aggregated group predictions outperform both sources at most points in time. The implication is that forecasters can get better predictions asking individuals who they think will win rather than who they want to win, especially more than a month or so before election day.

After reviewing the existing work on WT in elections, we describe our theoretical perspective and several open questions that our study helps to address. We then describe our survey procedure and data, followed by the empirical results on individual accuracy and prediction. Last, we compare the accuracy of our aggregated survey predictions with Intrade and 538.

Wishful Thinking in Elections

Existing Work on Wishful Thinking in Elections

What individuals want influences what they believe. In evaluating and constructing arguments, for instance, "[t]here is considerable evidence that people are more likely to arrive at conclusions that they want to arrive at" (Kunda 1990, 480). Preferences interfere with a variety of cognitive processes, including memory, the perception of control, and information processing (Eroglu and Croxton 2010; Kopko *et al*. 2011; Krizan and Windschitl 2007).

We focus on the effect of preferences on expectations, specifically the link between political support and electoral prediction. In numerous experiments and surveys, subjects display WT bias, a tendency to exaggerate the likelihood of desired events (see Krizan and Windschitl 2007 for a review). Cantril (1938) demonstrates WT in the prediction of social and political events, such as the outcome of the Spanish Civil War. Babad (1987) finds that 93 percent of soccer fans expect their favored team to win, which extends to betting behavior (Babad and Katz 1991). WT also holds among experts anticipating events, such as physicians (Poses and Anthony 1991), politicians (Lemert 1986), and investment managers (Olsen 1997). Further, WT bias is minimally affected by instructions to be objective and rewards for accuracy (Babad and Katz 1991; Krizan and Windschitl 2007).

Electoral prediction is the best developed strand of the literature on WT. As far back as the 1930s, Hayes (1936) showed that both voters' and party leaders' preferences strongly correlated with their expectations of election winners. In the 1932 U.S. presidential election, 93 percent of Roosevelt supporters thought he would win, whereas 73 percent of Hoover supporters predicted a Hoover win. Using American National Election Studies data, Lewis-Beck and Skalaban (1989) and Lewis-Beck and Tien (1999) find a consistent preference–expectation link in each U.S. presidential election since 1956. Similar results are found for expectations about public referenda (Granberg and Brent 1983; Lemert 1986; Rothbart 1970), as well as elections in Sweden (Granberg and Holmberg 1988; Sjöberg 2009), New Zealand (Babad, Hills, and O'Driscoll 1992; Levine and Roberts 1991), Israel (Babad 1997; Babad and Yacobos 1993), Canada (Johnston *et al*. 1992), the Netherlands (Irwin and van Holsteyn 2002), and Great Britain (McAllister and Studlar 1991; Nadeau, Niemi, and Amato 1994).[1]

Why do preferences affect expectations? Krizan and Windschitl (2007) posit that preferences affect three distinct stages of information processing: searching for evidence, evaluating the strength of that evidence, and formulating a final

[1] A problem in interpreting WT results is determining the direction of causation, since bandwagoning may increase support for the expected election winner (Bartels 1985; McAllister and Studlar 1991; Nadeau, Niemi, and Amato 1994). However, the weight of evidence indicates that the main causal pathway between preferences and expectations is through WT bias (Johnston *et al*. 1992; Krizan, Miller, and Johar 2010).

opinion. Generally, facts confirming a desired conclusion are more available in memory and individuals tend to be satisfied with a conclusion once they have constructed a plausible justification for it (Kunda 1990). Moreover, projection bias leads people to assume others have similar political opinions and attributes as themselves (Bartels 1985; Ross, Greene, and House 1977). As a result, they exaggerate the extent to which others favor their chosen candidate or cause. A similar bias arises from the selective sample of associates (Gentzkow and Shapiro 2011; Huckfeldt and Sprague 1987, 1995; Regan and Kilduff 1988) and information sources, such as newspapers and blogs (Gentzkow and Shapiro 2011; Redlawsk 2004). Finally, people formulate beliefs that the "right" candidate will be chosen as a form of dissonance reduction (Regan and Kilduff 1988).

Our Theoretical Perspective

Although the literature has successfully established a preference–expectation link in elections, there remain a number of open questions concerning how WT bias and accuracy vary between individuals and across time. We now outline our theoretical perspective and summarize our main findings. In the following subsection, we expand on the set of open questions that our study addresses.

Since the literature has concentrated on establishing WT's existence, there has been relatively little consensus on what individual traits mitigate or amplify WT bias (Babad, Hills, and O'Driscoll 1992; Dolan and Holbrook 2001; Eroglu and Croxton 2010).[2] We argue that two factors affect its strength: individual sophistication and social influence.

First, more educated and sophisticated individuals should perform better at objectively gathering and evaluating information. The most consistent result in the existing literature is that education reduces WT bias (Babad, Hills, and O'Driscoll 1992; Dolan and Holbrook 2001; Granberg and Brent 1983; Hayes 1936; Lewis-Beck and Skalaban 1989). We confirm the moderating effect of education, concurring with Granberg and Brent (1983) that education provides greater exposure to outside views and more experience with objectively evaluating information.

In addition to education, we test the effect of a novel variable (*incoherence*) that proxies for a general lack of numerical sophistication. This is constructed by asking individuals for state predictions involving complex conditionals (such as Obama's likelihood of winning Maine given that he wins Florida) and calculating their numerical incoherence. An advantage of this variable is that it is computed purely from each individual's predictions, rather than the

[2] There is mixed evidence that WT is exacerbated by partisan intensity (Dolan and Holbrook 2001; Granberg and Brent 1983; Levine and Roberts 1991) and reduced by knowledge (Babad 1997; Dolan and Holbrook 2001; Sjöberg 2009). However, the act of voting is found to increase WT bias (Frenkel and Doob 1976; Regan and Kilduff 1988).

individual's self-report of his or her background. It is thus a more objective indicator of numerical fallibility. We hypothesize that *incoherence* will predict lower accuracy and more WT bias. Further, we expect that improvements in forecasting accuracy over time—as more information is acquired and polling becomes more accurate—will be concentrated among the most sophisticated individuals. We confirm each of these hypotheses in our results.

Second, voters' residences and social interactions should strongly influence electoral expectations. Because of data limitations, past work has neglected the role of surroundings.[3] This is a considerable oversight given the central role that social networks play in dispersing political information (Borgatti and Cross 2003; Gentzkow and Shapiro 2011; Huckfeldt and Sprague 1987, 1995; Regan and Kilduff 1988). As Huckfeldt and Sprague (1995, 124) argue, "[p]olitical behavior may be understood in terms of individuals who are tied together by, and located within, networks, groups, and other social formations that largely determine their opportunities for the exchange of meaningful political information." Given its heterogeneous population and relatively decentralized media environment, the United States is an ideal location for a study of residence effects on prediction.

To investigate social influence, we employ our large and geographically diverse sample (including individuals from all the 50 states) to test how Obama's vote share in respondents' home states influence their predictions. All things equal, a voter in California will have more social contacts who favor Obama than a voter in Wyoming. Although individuals tend to seek out like-minded partners for political discussion, this selection effect is not strong enough to erase the influence of the surrounding majority (Huckfeldt and Sprague 1995, 124-35). We consider two alternative hypotheses on how this social interaction influences individual forecasts, one concerning the bias of electoral information and the other the volume of information.

A simple hypothesis is that voters from Obama-supporting states will express more positive expectations of Obama's chances, as they become influenced by their associates' optimism and surrounding signs of political support (Uhlaner and Grofman 1986). As Granberg and Holmberg (1988, 149) claim, voters may tell themselves, "[a]s my state goes, so goes the nation." In this view, WT is contagious and mutually reinforcing, just as Sunstein (2009) argues that being surrounded by like-minded associates increases opinion extremism.

We instead find support for a very different relationship between residence and prediction. Stronger home-state Obama support in fact improves accuracy

[3] A partial exception is Meffert and others (2011), which finds that West Germans and Berliners are marginally better predictors of German elections. Other work compares how individuals predict elections in their own states versus national elections. In New Zealand, Levine and Roberts (1991) and Babad, Hills, and O'Driscoll (1992) find that WT bias is stronger for local results compared to national ones. However, Granberg and Brent (1983) do not find this effect for the United States, hypothesizing that stronger bias and greater knowledge balance out.

and reduces WT bias among both Democrats and Republicans. As a result, living in a pro-Obama state makes Democrats less optimistic for Obama's chances across the country. This finding holds even after controlling for state levels of education, income, media consumption, and campaign spending.

We interpret this result in terms of the *volume* of information exchanged.[4] Given Obama's lead throughout the survey period, Obama supporters were more active in discussing politics and the election specifically (Fernandes *et al.* 2010; Winneg 2009, 95). This inevitably had informational consequences for neighbors and social contacts, as political conversations directly increase knowledge and encourage further media exposure, information seeking, and discussion (Eveland and Thomson 2006; Huckfeldt and Sprague 1987, 1995; McClurg 2006). For instance, among young adults during the 2008 U.S. presidential campaign, "individuals' frequency of political talk with parents, close friends, significant others, and siblings was found to be a predictor of their political media diet" (Rill and McKinney 2011, 64).[5] Being surrounded by Obama voters thus heightened informational exposure about the campaign and led to more accurate electoral expectations.

Other Open Questions

We have just covered our expectations for which individual factors mitigate WT bias and how residence affects individual predictions. We now consider four additional open questions that our study addresses.

What Individual Factors Affect Predictive Accuracy?

As Eroglu and Croxton (2010) note, the literature on WT offers few consistent conclusions on the factors predicting individual forecasting accuracy. As in several previous studies (Babad 1997; Dolan and Holbrook 2001; Sjöberg 2009), we analyze the common demographic variables of sex, age, and education. We also study the effects of two types of self-described knowledge, party identification, and whether respondents are judging their own states. Of greater novelty is our inclusion of *incoherence* and state residence.

Does Wishful Thinking Hold for Estimating Probabilities?

The measurement technique for each side of the preference–expectation link varies across previous studies, with minimal effect on findings.[6] To measure

[4] As this is a novel result, we believe it should prompt further research that can confirm this pattern and more finely trace the causal mechanisms.

[5] McDevitt and Kiousis (2007) also find that classroom discussions about politics increase political conversations among students at home.

[6] To measure preferences, studies variously ask for party identification (Lemert 1986; Lewis-Beck and Skalaban 1989; Sjöberg 2009), vote intention (Hayes 1936; Irwin and van Holsteyn 2002; Lewis-Beck and Skalaban 1989), or candidate evaluations (Babad 1997; Babad, Hills, and O'Driscoll 1992; Krizan, Miller, and Johar 2010).

expectations, nearly all studies ask respondents to predict the election winner.[7] The current study differs by asking individuals for their probability estimates of who will win various states. Results from experimental psychology indicate that this represents a hard case for finding a WT effect (Bar-Hillel and Budescu 1995; Krizan and Windschitl 2007; Price and Marquez 2005). In fact, our results appear to be the first in any empirical study to find a robust WT effect for estimating probabilities.

How Do Individual Predictions Change over Time?

A few existing studies demonstrate that electoral forecasting accuracy improves as election day approaches (Dolan and Holbrook 2001; Krizan, Miller, and Johar 2010; Lewis-Beck and Skalaban 1989; Lewis-Beck and Tien 1999). However, there exists little work on how other patterns of individual prediction change. For instance, does WT bias increase or decrease closer to the election? Do all voters increase their accuracy over time or is the effect isolated among more sophisticated voters? Taking advantage of our large sample, featuring responses over the two months prior to election day, we investigate how accuracy evolved throughout the election cycle.

How Do Group Predictions Compare to Other Forecasts?

Controversy exists over the relative predictive power of expert forecasting, polls, and prediction markets (Leigh and Wolfers 2006). An underinvestigated method of electoral prediction is the aggregation of individual expectations. According to the "wisdom of crowds" hypothesis (Surowiecki 2004), group estimates should be highly accurate, outperforming even political experts. We address two questions along these lines: first, how should individual predictions be aggregated to maximize forecasting accuracy? Second, how does the predictive power of these group estimates compare to prediction markets and probability estimates derived from polls? We compare aggregated group estimates to the predictions provided by Intrade and 538 at several points in time. We find that a group aggregation that adjusts for the influence of prospect theory outperforms both sources at most points in time.

The Survey and Data

The Survey Procedure

We established a website to collect probability estimates of state outcomes in the two months prior to the 2008 U.S. presidential election, beginning immediately after the Republican National Convention on September 4.

[7] Some studies additionally ask for winning margins (Lemert 1986; Sjöberg 2009), seat totals in parliamentary elections (Babad and Yacobos 1993), or confidence levels (Krizan, Miller, and Johar 2010).

Advertisements ran on politically oriented websites to attract respondents, but none of these websites was affiliated with a political party or candidate. Cash prizes were offered to respondents with the highest accuracy as an incentive for individuals to reveal their true beliefs.

Each participant was given an independent, randomly generated survey. A given survey used a randomly chosen set of seven (out of 50) states. Each respondent was asked 28 questions, seven of which asked for the likelihood that a particular candidate would win each state. For instance, a respondent could be asked, “What is the probability that Obama wins Indiana?” The remaining 21 questions involved conjunctions, disjunctions, and conditionals concerning election outcomes in the seven states. For instance, a respondent could be asked, “What is the probability that McCain wins Florida supposing that McCain wins Maine?” These more complex questions allow us to measure the probabilistic coherence of each judge. For each respondent, we randomized the seven states, the order of simple and complex events, and the name used in each question, McCain or Obama. Respondents provided probability estimates running from 0 to 100 percent. In total, we collected 19,215 complete sets of predictions.

As with any data collection procedure, positives and negatives come with employing an online survey. On the positive side, we attain a size and variation in our sample that would be infeasible using other methods. On the negative side, there are concerns that the sample is partially self-selected and therefore nonrepresentative, although not necessarily more so than a sample of college students. In particular, our sample skews toward Democrats, the highly educated, and the politically attentive, and we therefore control for these factors in all models.

Although the sample’s composition should be kept in mind, it is unlikely to yield significant bias in comparisons among our subjects. First, we obtain very similar results on the size of WT bias (and its variation with education) compared to past studies. This bolsters our confidence that the more novel results have external validity. Second, we obtain results on WT bias by comparing Republicans and Democrats, who in our survey are very well-balanced on all explanatory variables. For every variable, each group’s mean is within a half-standard-deviation of the other group’s mean. Last, the sample’s composition does not in any way negate the use of our procedure as a forecasting tool, as it is easily replicable in future elections.

Dependent Variables

Our analysis focuses on two dependent variables: a measure of each respondent’s overall predictive accuracy and the respondent’s predictions for each state. For both measures, we only incorporate the seven simple probability estimates (i.e., none of the complex questions).

To measure individual *accuracy*, we use the negative log-odds of the Brier Score (Brier 1950; Predd *et al.* 2008), which measures the mean squared error of the predictions. Because the Brier Score runs strictly from 0 to 1, we use a log-odds transformation to make the measure suitable for ordinary least squares (OLS) regression. We take the negative so that larger values correspond to more accurate judges. Formally:

Definition 1. Let P_i be the probabilistic prediction of an election and let $O_i \in \{0,1\}$ be the actual outcome. The Brier Score is defined as $BS = \frac{1}{7}\sum_{i=1}^{7}(O_i - P_i)^2$. Accuracy is defined[8] as $-\log\frac{0.01+BS}{1.01-BS}$.

Our second dependent variable is the probability estimate that each individual assigned to Obama winning a state (*Prediction for Obama*). For the OLS regressions, we again use a log-odds transformation.

Explanatory Variables

We collected respondents' demographic information (gender, *age*, and *education*[9]), their place of residence (among 50 states or outside the United States), their party identification (*Republican*, *Democrat*, or *independent*), the day they filled out the survey (*Day*), and numerical self-ratings (on a 100-point scale) of *general political knowledge* and their familiarity with the election (*election knowledge*). Our study employs party identification as the measure of political preference, with the advantage that party ID is relatively stable over the long term (Green and Palmquist 1994; Sears and Funk 1999) and thus less susceptible to reverse causation. Of the 19,215 survey responses, 16,082 include complete personal information, with 15,142 of these located inside the United States. The latter total corresponds to 105,994 separate state predictions.

Finally, using all the 28 predictions per individual, we calculated each respondents' probabilistic incoherence as a measure of numerical sophistication.[10] Since they were asked to judge complex conditional probabilities, individuals often supplied mathematically impossible probability estimates. For instance, they could predict that Obama had a 50 percent chance of winning Virginia and a 60 percent chance of winning both Virginia and California. *Incoherence* measures how far a judge's forecast departs from a logically coherent estimate. To calculate this, we computed the coherent forecast closest to the individual's predictions using the Coherent Approximation Principle proposed by Osherson and Vardi (2006).[11] *Incoherence* is the summed squared distance between this coherent forecast and the original forecast. Summary statistics for all variables are displayed in Table 1.

[8] We use the .01 adjustment to avoid infinite values when *BS* is exactly 0 or 1. Results are not sensitive to this parameter.

[9] This was measured on a nine-point scale running from no high school to a professional degree. We include it in the regressions as an ordinal variable. Using dummies for each category returns similar results.

[10] The measure may also track how much attention the respondents were applying to the survey.

[11] See Predd and others (2008) and Wang and others (2011) for past applications.

Table 1. Summary Statistics

Variable	Mean	Std.Dev.	Min.	Max.	n
Accuracy	2.600	.926	–1.736	4.615	19,215
Prediction for Obama (log-odds)	.226	2.823	–4.615	4.615	134,505
Prediction for Obama	.527	.377	0	1	134,505
Obama vote share	.560	.072	.334	.730	16,884
Republican	.072	.258	0	1	17,763
Democrat	.713	.452	0	1	17,763
Independent	.215	.411	0	1	17,763
General political knowledge	81.015	15.233	0	100	19,215
Election knowledge	77.303	19.191	1	100	18,682
Incoherence	.299	.403	0	3.671	19,215
Male	.743	.437	0	1	18,821
Age	38.780	14.575	13	99	19,215
Education	6.865	1.804	2	9	18,659
Judging residence	.127	.333	0	1	18,288
Residence education	1.256	.082	1.060	1.432	16,884
Residence income ($10,000)	3.829	.520	2.787	5.159	16,884
Residence newspapers	.169	.075	.08	.40	16,884
Residence campaign spending	1.367	1.966	0	13.062	16,884
Day	–15.589	17.233	–59	0	19,215

Empirical Results

We now discuss our empirical results on individual *accuracy* and state forecasts. The former captures how well individuals made predictions and the latter the direction and magnitude of predictive bias. We then consider how these patterns changed as election day approached.

Individual Accuracy

Models 1-3 of Table 2 present the main results for individual accuracy. The OLS models predict *accuracy* from the explanatory variables and four sets of added control variables. It is necessary to account for both the day the individual was judging and the specific states being judged. In addition, states display different patterns across time for how easy they were to predict. The models thus add fixed effects for each day and each of the seven states being judged, as well as interactions of *Day* (as a continuous variable) and Day^2 with the state fixed effects. This sets a baseline for the difficulty of predicting each state at each point in time (modeled as a quadratic function of *Day*). The parentheses beside each coefficient show *t*-values based on robust standard errors clustered by *Day*. We also estimated the models by dichotomizing the predictions and testing how many of the seven states each individual predicted correctly. All of the results from Table 2 hold.

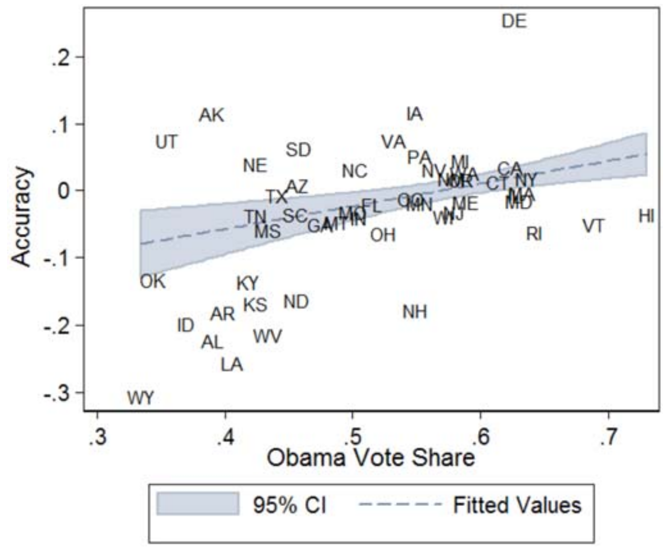
The first result worth highlighting is the effect of party identification. Democrats performed better than independents, and Republicans performed

Table 2. OLS Regressions of Accuracy and Prediction for Obama

	Accuracy			Prediction for Obama (log-odds)	
	(1)	(2)	(3)	(4)	(5)
Obama vote share	.345*** (4.11)	.406** (3.12)		−.076 (−1.02)	
Republican × Obama vote share			.808** (3.10)		.595* (2.11)
Democrat × Obama vote share			.391** (3.38)		−.213* (−2.45)
Independent × Obama vote share			.033 (.23)		.102 (.62)
Republican	−.199*** (−6.74)	−.199*** (6.60)	−.626*** (−3.77)	−.265*** (−10.01)	−.535** (−2.88)
Democrat	.067*** (4.04)	.067*** (4.02)	−.132 (−1.29)	.041** (3.02)	.216* (2.06)
General political knowledge	.002** (3.05)	.002** (3.05)	.002** (3.04)	.001 (1.46)	.001 (1.46)
Election knowledge	.010*** (26.00)	.010*** (26.04)	.010*** (25.89)	−.001** (−2.69)	−.001** (−2.70)
Incoherence	−.177*** (−6.94)	−.177*** (−6.96)	−.176*** (−6.85)	.080*** (3.85)	.080*** (3.87)
Male	.182*** (17.83)	.182*** (17.80)	.181*** (17.69)	−.065*** (−4.97)	−.065*** (−4.97)
Age	−.007*** (−10.41)	−.007*** (−10.56)	−.007*** (−10.41)	.002*** (5.84)	.002*** (5.85)
Education	.008 (1.62)	.008 (1.63)	.008 (1.61)	−.018*** (−5.42)	−.018*** (−5.41)
Judging residence	−.027 (−1.39)	−.027 (−1.39)	−.027 (−1.42)		
Residence education		−.053 (−.37)			
Residence income		−.11 (−.54)			
Residence newspapers		.156 (1.80)			
Residence campaign spending		.002 (.69)			
Day fixed effects (FEs)	Y	Y	Y	Y	Y
Judged State FEs	Y	Y	Y	Y	Y
J. State FEs × Day	Y	Y	Y	Y	Y
J. State FEs × Day^2	Y	Y	Y	Y	Y
n	15,142	15,142	15,142	105,994	105,994
Adjusted R^2	.332	.332	.332	.725	.725
BIC	34,690.5	34,695.6	34,694.5	385,413.3	385,422.3

Notes: Models 1-3 predict individual *accuracy*. t-Statistics (based on robust standard errors clustered by *Day*) are shown in parentheses. Models 4-5 estimate the *Prediction for Obama* (log-odds) given for seven states per individual. t-Statistics (based on robust standard errors clustered by individual) are shown in parentheses. * $p < .05$; ** $p < .01$; *** $p < .001$.

Figure 1.
Accuracy by Residence



Notes: Figure 1 shows state residence fixed effects for *accuracy* against *Obama vote share* after accounting for the standard controls. Non-U.S. respondents are the reference group. The dotted line is a linear fit weighted by the state's number of respondents. Individuals from Obama-supporting states are significantly more accurate (n = 16,884).

considerably worse. In fact, the difference between Republicans and independents is about three times the difference between Democrats and independents. As we explore below, WT is the main cause—Democrats were optimistic about Obama's chances, and the election ended up being very successful for him.

State Residence. Consistent with our expectation that social surroundings can matter, model 1 finds that respondents from states with a higher *Obama vote share* (his portion of the two-party vote) were significantly more accurate. Non-U.S. respondents are dropped from this model's sample, but on average they were even more accurate than individuals in states won by Obama. A more detailed picture is provided by Figure 1. State fixed effects for *accuracy* are plotted against the state's *Obama vote share*. The dotted line displays a weighted linear fit of the relationship and the shaded area the 95 percent confidence interval.[12]

[12] The linear fit weights by the number of respondents in each state. This is equivalent to an individual-level regression using standard errors clustered by state.

Obama vote share is correlated with several other state characteristics that may also increase accuracy. To see if the effect is robust, model 2 controls for levels of education, income, newspaper consumption, and campaign spending in respondents' home states. *Residence education* is the summed fractions of state residents aged 25 or older with high school, bachelor, and advanced degrees. *Residence income* is per capita income (in $10,000). *Residence newspapers* is the per capita circulation of daily newspapers. All three are 2008 figures taken from the U.S. Census Bureau (2011). *Residence campaign spending* is summed per capita ad spending (in U.S. dollars) from the two presidential campaigns.[13] The first three are positively correlated with Obama support, but the coefficient on *Obama vote share* only increases in magnitude in model 2.

Finally, model 3 separates out the effect of *Obama vote share* by party identification. Previewing results below, *Obama vote share* improves the accuracy of Republicans and Democrats, but not independents. Moreover, the effect is strongest for Republicans.

Other Controls. Results for the remaining control variables are highly consistent across models. Higher values of self-described knowledge improve *accuracy*, with the effect of *election knowledge* greater in magnitude than *general political knowledge*. Thus, respondents were good judges of their own predictive ability. As expected, the two measures of sophistication—higher *education* and lower *incoherence*—predict greater *accuracy*, although *education*'s effect is insignificant. Surprisingly, individuals are less accurate at judging their home states, although not significantly.[14] Finally, men and younger individuals are found to be more accurate.

Individual Predictions

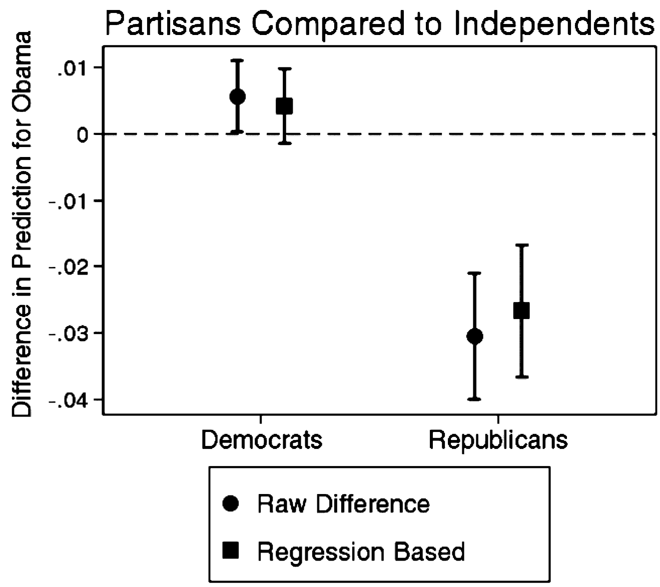
Models 4-5 in Table 2 and the five models in Table 3 directly test for the presence and magnitude of WT bias by looking at individual predictions for Obama. We use the same set of controls as for *accuracy* and cluster standard errors by individual survey to account for differences across individuals.

As evidence for WT bias, model 4 shows that the coefficient on *Republican* is negative and the coefficient on *Democrat* is positive. That is, party members rated their candidate's likelihood of winning higher. Figure 2 shows the differences in mean estimates provided by Democrats and Republicans compared with independents, averaged across the 50 states being judged and calculated with and without the control variables. On average, Democrats overestimated Obama's chances in each state by .6 percent relative to

[13] These data are available from CNN (2008).

[14] In other results, we source this effect mostly to Democrats significantly overestimating Obama's chances in their home states, perhaps being swept away by the highly visible enthusiasm of the Obama campaign. These results are available from the authors on request.

Figure 2.
Difference of Mean Predictions



Notes: Figure 2 shows the difference in mean *prediction for Obama* between Democrats and independents and between Republicans and independents. The circle points represent the simple difference of means. The square points show the difference of means after accounting for the standard control variables. The bars show 95 percent confidence intervals. All party identifiers display wishful thinking bias, but the effect is stronger for Republicans (n = 16,489; 15,099).

independents, whereas Republicans underestimated his chances by 3.1 percent. Again, we speculate that the larger bias among Republicans stems from Obama's ascendancy during the period.

State Residence. Being surrounded by Democrats does not have the same straightforward effect as personal party identification. As seen in model 4, a higher *Obama vote share* actually leads to slightly *lower* expectations for Obama. Model 5 shows what is happening—higher *Obama vote share* leads Republicans to raise their expectations for Obama but has the opposite effect on Democrats. In other words, *Obama vote share* reduces WT bias.

Size of Wishful Thinking Bias. Table 3 further investigates variation in WT bias. The sample includes only Republicans and Democrats, thus the coefficient on *Democrat* measures the difference in their average predictions for Obama, an appropriate measure of WT bias. In each regression, *Democrat* is further

Table 3. OLS Regressions of Size of Wishful Thinking Bias

	Prediction for Obama (log-odds)				
	(1)	(2)	(3)	(4)	(5)
Democrat × education	−.052*** (−3.43)				−.047*** (−3.35)
Democrat × incoherence		.383*** (4.06)			.338*** (3.82)
Democrat × general political knowledge			.007*** (4.14)		.008*** (4.31)
Democrat × Obama vote share				−.792** (−2.68)	−.596* (−2.08)
Democrat	.644*** (5.99)	.182*** (6.02)	−.274* (−1.96)	.742*** (4.39)	.207 (.97)
Obama vote share	−.127 (−1.53)	−.139 (−1.68)	−.128 (−1.54)	.581* (2.06)	.397 (1.45)
General political knowledge	.001 (1.06)	.001 (1.23)	−.006*** (−3.46)	.001 (1.06)	−.006*** (−3.59)
Election knowledge	−.001** (−3.02)	−.001** (−3.06)	−.001** (−2.99)	−.001** (−3.01)	−.001** (−3.04)
Incoherence	.065** (2.91)	−.284** (−3.10)	.068** (3.01)	.066** (2.94)	−.239** (−2.79)
Male	−.064*** (−4.44)	−.062*** (−4.32)	−.064*** (−4.48)	−.063*** (−4.36)	−.066*** (−4.57)
Age	.003*** (5.89)	.003*** (5.82)	.003*** (5.71)	.003*** (5.86)	.003*** (5.68)
Education	.026 (1.77)	−.020*** (−5.45)	−.020*** (−5.26)	−.020*** (−5.34)	.022 (1.62)
Day fixed effects (FE)	Y	Y	Y	Y	Y
Judged State FEs	Y	Y	Y	Y	Y
J. State FEs × day	Y	Y	Y	Y	Y
J. State FEs × day^2	Y	Y	Y	Y	Y
n	83,895	83,895	83,895	83,895	83,895
Adjusted R^2	.729	.729	.729	.729	.729
BIC	304,667.0	304,626.1	304,664.7	304,686.5	304,595.3

Notes: The models estimate the *Prediction for Obama* (log-odds) given for seven states per individual, using a sample of party identifiers. The models investigate what reduces or exacerbates wishful thinking bias. t-Statistics (based on robust standard errors clustered by individual) are shown in parentheses. We find that *education* and *Obama vote share* reduce wishful thinking bias, whereas *incoherence* and self-rated knowledge increase it.
* $p < .05$; ** $p < .01$; *** $p < .001$.

interacted with another variable, thereby testing how WT's magnitude fluctuates. Since the direct impact of *Democrat* is positive, a negative coefficient on the interaction term indicates a reduction of WT bias.

Models 1 and 2 confirm our expectations on individual sophistication. Education reduces WT bias, the most consistent result in the previous literature. By contrast, *incoherence* exacerbates it—less numerically sophisticated respondents were especially influenced by party preference. Surprisingly, model 3 shows that self-rated knowledge increase WT bias.[15] We hypothesize that this is because knowledge proxies for interest in the campaign and by extension partisan intensity.[16]

Model 4 confirms that *Obama vote share* reduces WT bias, supporting our argument that social surroundings and information exchange can reduce bias. The effect is substantial—the estimation implies that a move from Wyoming to Hawaii reduces WT bias more than changing from a high school education to a doctorate. As above, this finding is robust to including interaction terms with the levels of education, income, newspaper consumption, and campaign spending in respondents' home states. Last, model 5 controls for all four interaction terms simultaneously. Each of the effects remains significant.

Figure 3 displays state-by-state results on WT bias. Using a sample of party identifiers and accounting for the standard controls, the figure shows the difference in the average predictions of Republicans and Democrats plotted against *Obama vote share*. The dotted line displays a weighted linear fit of the relationship and the shaded area the 95 percent confidence interval.[17] WT bias is positive in all but four states, but greater Obama support is associated with a smaller WT effect among the state's residents.

Variation by Day

Clocking from 59 days prior to the election up until the morning of election day, our data provide a rich picture of how individual predictions change as time passes and new information is acquired. Figure 4 shows the average *accuracy* for each day in the sample, combined with a linear fit. Despite some noise, individuals became significantly better at prediction as time progressed.

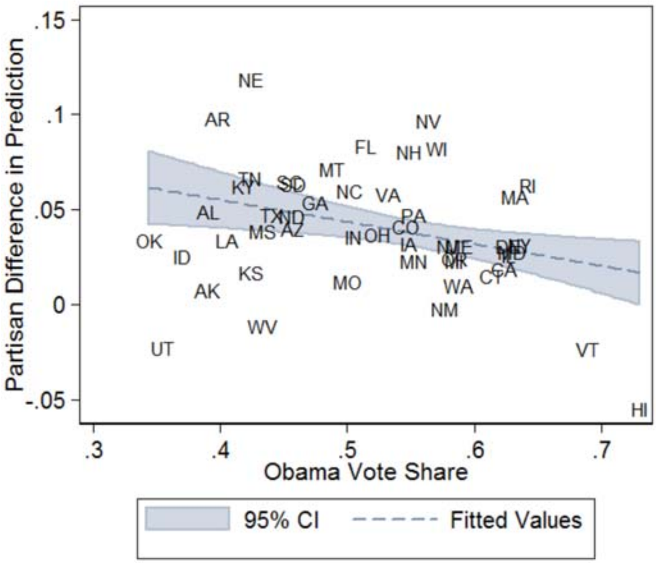
We now investigate how this improvement is divided across individuals. We categorize respondents into three equally sized groups according to their level of *incoherence*. Figure 5 shows *accuracy* averaged by *day* and *incoherence*

[15] The result for *election knowledge* is substantively identical.

[16] Knowledge increases WT bias but still improves *accuracy* because it reduces the variance of predictions. Since *accuracy* is calculated from the squared error of predictions, it is a function of both squared bias and variance.

[17] The linear fit weights by the number of respondents in each state. This is equivalent to an individual-level regression using standard errors clustered by state.

Figure 3.
Wishful Thinking Effect by Residence



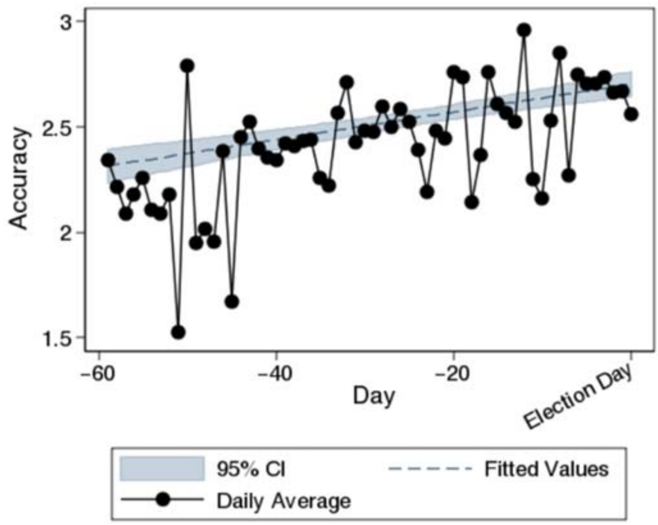
Notes: Figure 3 shows wishful thinking bias (the difference between Democrats and Republicans in average *prediction for Obama*) in each state plotted against *Obama vote share*. The difference is calculated after accounting for the standard control variables, with the exception of the party dummies. The dotted line is a linear fit weighted by the state's number of respondents (n = 16,884).

level. For ease of interpretation, *accuracy* is smoothed using a loess curve with a bandwidth of .1. The least incoherent group improved markedly and consistently over time. In contrast, the bottom two-thirds of respondents improved their average *accuracy* marginally, if at all. Hence, the utilization of information as the campaign season progressed was highly concentrated among more sophisticated observers.

Dividing *accuracy* by *day* and party identification in Figure 6, we find that Democrats and independents were consistently more accurate than Republicans. Further, Democrats improved steadily over time, whereas Republicans were no more accurate 20 days prior to election day than 59 days prior. However, Republicans rapidly caught up to Democrats about two weeks prior to election day, perhaps indicating an unwillingness to acknowledge Obama's advantage until his national victory was all but certain.

Finally, Figure 7 shows the smoothed average of *prediction for Obama* by *day* and party identification. For clarity, *prediction for Obama* is the probability

Figure 4.
Accuracy by Day



Notes: Figure 4 shows average *accuracy* by *day*, along with a linear fit weighted by sample size. The period begins immediately after the Republican National Convention on September 4, 2008. Respondents steadily improved their accuracy over time (n = 19,215).

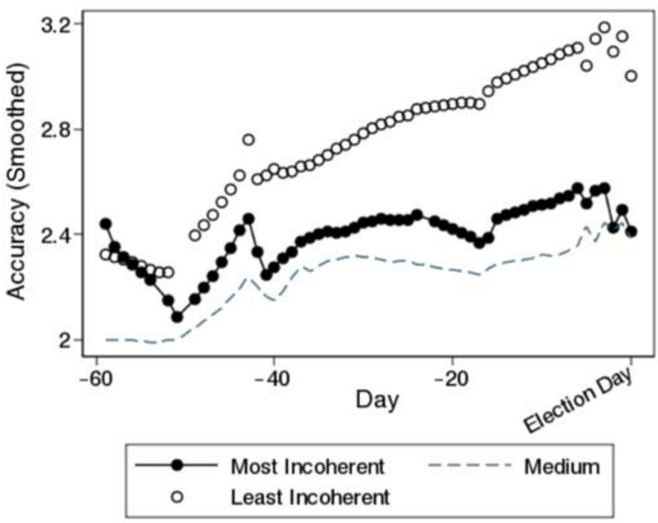
estimate rather than the log-odds transform. The difference between Democrats and Republicans tracks the strength of WT bias. Except for very early and very late in the period, WT bias is fairly consistent across time and hovers around 4-5 percent.

Testing the "Wisdom of Crowds"

Macroeconomic voting models, polls, and prediction markets remain the most common methods of forecasting elections. Political scientists have developed forecasting models using factors like incumbency, macroeconomic variables (Abramowitz 2004; Fair 2002), and battle deaths (Hibbs 2008).[18] Polls are of course the most common predictive tool among the public and the media (Irwin and van Holsteyn 2002), with their accuracy increased by suitable aggregation (Jackman 2005; Lock and Gelman 2010). In prediction markets, individuals purchase shares that pay off depending on the outcomes of specific

[18] See Jones (2008) and Walker (2008) for reviews.

Figure 5.
Accuracy by Day and Incoherence Level

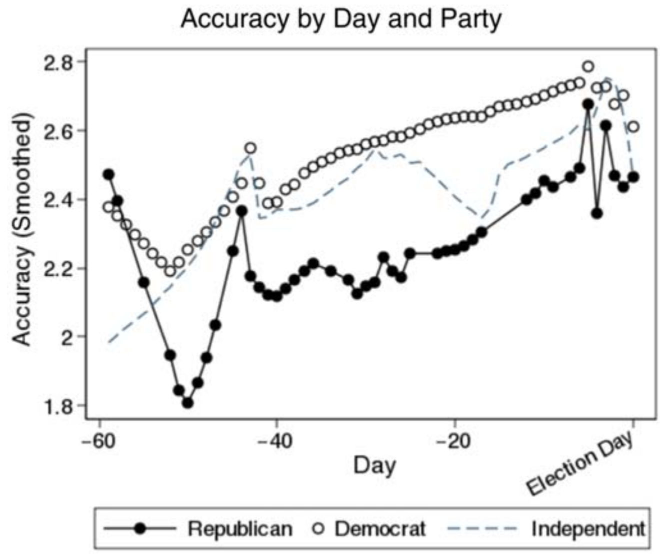


Notes: Figure 5 shows average *accuracy* by *day* and level of *incoherence* (split into three equally sized groups). The lines are smoothed using a loess curve with a bandwidth of .1. The improvement in *Accuracy* over time is heavily concentrated among the least incoherent (most numerically sophisticated) respondents (n = 19,215).

elections. The share prices can thus be interpreted as expected likelihoods of the electoral outcomes, prompting a great deal of interest in the markets' predictive powers (Ray 2006; Surowiecki 2004; Tziralis and Tatsiopoulos 2007; Wolfers and Zitzewitz 2004). There is disagreement over the relative accuracy of forecasting models, polls, and prediction markets, with Leigh and Wolfers (2006) giving the edge to prediction markets and Jones (2008) and Erikson and Wlezien (2008) finding polls to be the most accurate.

We test an alternative forecasting method supported by the "wisdom of crowds" hypothesis that group predictions should be highly accurate (Surowiecki 2004). We compare the accuracy of group estimates derived from our sample with probability estimates provided by 538 (a poll aggregator run by Nate Silver) and Intrade (a prediction market), both of which were highly successful at predicting the 2008 election. These provide the best points of comparison as both sites predicted state outcomes at several points in time, whereas forecasts by political scientists generally focus on a single national estimate. Lewis-Beck and Tien (1999), Jones (2008), and Sjöberg (2009) are the only studies we know of that compare electoral forecasting accuracy between

Figure 6.
Accuracy by Day and Party



Notes: Figure 6 shows average *accuracy* by *day* and party identification. The lines are smoothed using a loess curve with a bandwidth of .1. Republicans were least accurate throughout but partially caught up immediately before election day (n = 17,763).

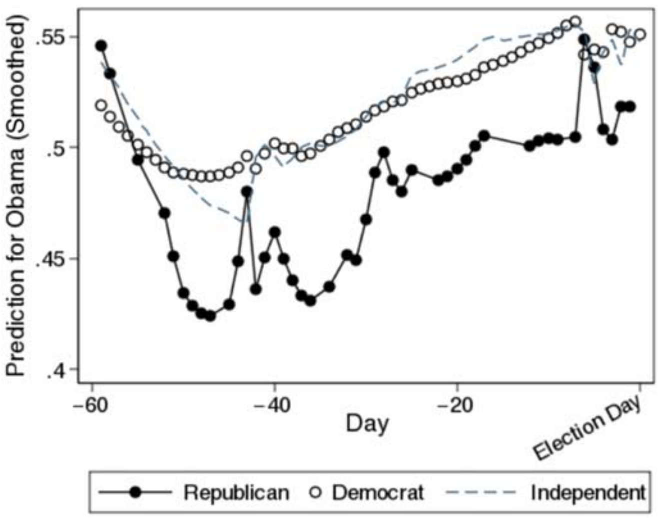
individual surveys and polls, whereas no previous study has compared surveys and prediction markets.[19]

As a first indication of group accuracy, Figure 8 shows how the median prediction for each state relates to the outcome (in terms of Obama's vote share in the state being judged). We expect an S-curve relationship, since even small vote margins translate into high likelihoods that a candidate will win a majority. This is indeed what we see in Figure 8. Despite including responses up to two months before the election, the median prediction was incorrect only for Indiana, although the median prediction for Missouri was exactly .5. Both Intrade and 538 predicted one state incorrectly immediately before the election.

For a fuller comparison with Intrade and 538, we break down the 60 days prior to the election into nine weeks. For Intrade, we compute the weekly mean of each state-level contract's bid and ask prices and interpret this mean as the market's predicted probability. For 538, we have four predictions at

[19] In the U.S. context, Lewis-Beck and Tien (1999) and Jones (2008) give a slight edge to polls over surveys of citizens and experts, respectively. In contrast, for the 2006 Swedish parliamentary election, Sjöberg (2009) finds that median predictions from a public survey outperformed polls. Lewis-Beck and Stegmaier (2011) and Murr (2011) show that aggregated expectations accurately predict British elections but do not compare this to any other method.

Figure 7.
Prediction for Obama by Day and Party



Notes: Figure 7 shows average *prediction for Obama* by *day* and party identification. The lines are smoothed using a loess curve with a bandwidth of .1. Although wishful thinking bias is evident throughout the two months (especially for Republicans), it was smaller in magnitude early and late in the period (n = 17,763).

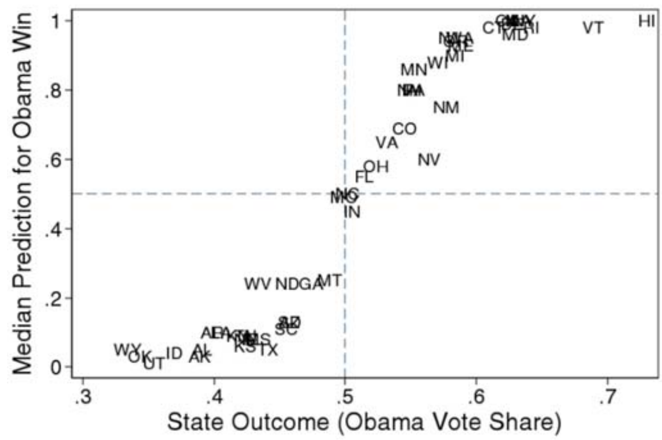
two-week intervals. We compare these predictions to weekly aggregations of our respondents' forecasts, using three methods: the mean, the median, and a sharpened median that accounts for the influence of prospect theory. For the latter, we use a transformation technique that corrects for the individual tendency to overweight small probabilities and underweight large probabilities (Kahneman and Tversky 1979; Tversky and Kahneman 1992). Our respondents tended to assign small but unrealistically high probabilities to extremely unlikely events like Obama winning Wyoming. We apply a sigmoid transformation so that the adjusted probability is:

$$f(P_i) = \frac{1}{1 + e^{B(0.5 - P_i)}}$$

where P_i is the original prediction and B is a tuning parameter we set at 10.[20] This shifts small probabilities toward 0 and large probabilities toward 1. We then take the median of these adjusted probabilities.

[20] This is a standard value that was not chosen to maximize accuracy. Different values of *B* give very similar results.

Figure 8.
Median Predictions for Each State



Notes: For each state, Figure 8 shows the median *prediction for Obama* against the state's outcome in *Obama vote share*. Note that *Obama vote share* now refers to the state being judged, not the respondent's residence. We find the expected S-shaped curve relating vote share and winning probability (n = 19,215).

Figure 9 compares the accuracy of the five prediction methods over time. First, the sharpened median outperforms the simple median, which in turn outperforms the mean of our respondents.[21] Second, the sharpened median is more accurate than Intrade in seven of nine weeks. Third, 538 is highly accurate close to election day, but is the worst of the five methods seven weeks prior.[22] In comparison, the sharpened median is virtually identical in accuracy immediately before the election and superior more than five weeks before the election. More complex aggregation procedures that weight judges by their coherence produce even more accurate results. However, we wish to emphasize that even simple aggregations of individual predictions can outperform the most sophisticated forecasting methods, especially early in the election period.

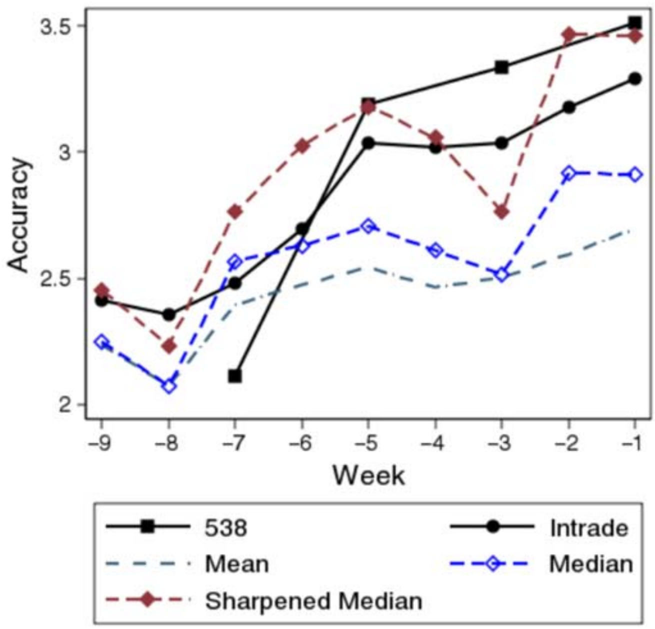
Conclusion

This study analyzed individuals' state-level predictions for the 2008 U.S. presidential election. We found that respondents who were Democratic,

[21] As Surowiecki (2004) explains, the median's superior performance compared to the mean follows from the logic of the Condorcet Jury Theorem.

[22] This is consistent with past findings that polls (the basis of 538's forecasts) are highly variable early in the election period but rapidly become more accurate closer to the election (Gelman and King 1993; Wlezien and Erikson 2002).

Figure 9.
Accuracy of Group Predictions versus Intrade and 538



Notes: Figure 9 compares the *accuracy* of our group survey predictions with Intrade and 538 over time. A sharpened median of our respondents (which accounts for prospect theory bias) outperforms Intrade in seven of nine weeks. It also outperforms 538 early in the election season and is nearly identical to 538 close to election day (n = 19,215).

younger, more numerically sophisticated, and gave themselves higher self-ratings of political knowledge were more accurate. We also uncovered strong support for WT bias in expectations, which was reduced by higher education and numerical sophistication. In addition, the vote share for Obama in respondents' home states predicted higher accuracy and lower WT bias.

The implication is that people are often fallible in allowing their desires to seep into their predictions, but this bias can be ameliorated by both individual education and greater information exchange. These results encourage further work on how political preferences relate to the formation of expectations. Future research can investigate the full range of personal characteristics and social influences that improve accuracy and mitigate or exacerbate WT.

Finally, we compared the forecasting accuracy of our survey group with predictions derived from polling and a prediction market. When estimates were sharpened to account for prospect theory, the group median was the most accurate at most points in time. This confirms that groups can be highly accurate even in the presence of individual bias, an optimistic sign for the epistemic capacity of democratic polities and markets to aggregate information (Surowiecki 2004). If further verified in future elections, the approach of aggregating individual expectations may greatly improve the accuracy of electoral forecasting for news organizations, campaigns, and political scientists. Although we relied on an online survey to maximize our sample size, a controlled sample balanced by party and location may be even more accurate. Our results also show improved accuracy after accounting for WT, respondent location, and numerical sophistication. It remains an open question whether an optimal aggregation technique can consistently outperform other forecasting methods at all points in time.

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