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Predicting 2016 State Presidential Election Results with a National Tracking Poll and MRP

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ABSTRACT

This paper presents state-level estimates of the 2016 presidential election using data from the ABC News and ABC News/Washington Post tracking poll and multilevel regression with poststratification (MRP). The multilevel models employ basic demographic variables at the individual level (gender, age, education and race) and a few state-level variables (past turnout, past party vote shares and the shares of blacks, Hispanics and evangelical white Protestants in each state's population), to estimate group-level turnout and vote preferences. Poststratification on 2015 American Community Survey estimates of demographic group sizes in each state results in correct predictions of the winner in 50 of 51 states and the District of Columbia (missing only Michigan) using data from 9,485 Americans interviewed in the weeks leading up to the election. While the approach does not perfectly estimate turnout as a share of the voting age population, popular vote shares or vote margins in each state, the model is more accurate than predictions published by polling aggregators or other MRP estimators, including in the number of races correctly projected and the root mean square error on the Clinton-Trump margin across states. The paper also reports how vote preferences changed over the course of the 18-day tracking period, compares subgroup-level estimates of turnout and vote preferences with the 2016 National Election Pool exit poll and summarizes the accuracy of the approach applied to the 2000, 2004, 2008 and 2012 elections. The paper concludes by discussing how researchers can make use of MRP as an alternative approach to survey weighting and likely voter modeling as well as in forecasting future elections.

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‡ The chart and footnote on p.20 have been updated from the conference paper.

I. OVERVIEW

Donald Trump's widely unexpected victory in the 2016 U.S. presidential election has raised questions about the accuracy of public opinion polling, the aggregation of polling into probabilistic election forecasts and the interpretation of election polling by data analysts, journalists and the general public. While national-level polls on average proved as accurate as in past elections in predicting the popular vote (with an average error on the margin of about 2 points), there were substantial polling errors at the state level, particularly in Midwestern swing states (Eten 2016; Silver 2017; Cohn, Katz and Quealy 2016). These significant misses, amplified by a proliferation of overconfident probabilistic forecasts, have (fairly or not) placed a cloud over the polling industry, provided ammunition to critics of survey research and led the leading industry association to study how the 2016 misses can be avoided in the future. This paper demonstrates the advantages of a statistical approach developed over the past two decades, multilevel regression with poststratification (MRP), in improving survey estimates in general and, specifically, in producing superior forecasts of election outcomes.

Our use of MRP combines statistical modeling of national-level survey data with census estimates of demographic group sizes at the state level to produce state-level turnout and candidate preference estimates (Park, Gelman and Bafumi 2004; Lax and Phillips 2009a, 2009b; Pacheco 2011; Ghitza and Gelman 2013). By combining individual-level demographic and state-level predictors of turnout and candidate preferences, the technique leverages subgroup-level similarities in electoral attitudes across geographical units (in this case, states). Through this partial pooling approach, MRP can provide highly accurate state-level estimates of voter intentions even with relatively small state-level sample sizes.

We focus chiefly on our implementation of MRP using survey data from the 2016 ABC News and ABC News/Washington Post tracking poll,[1] a national, probability-based RDD survey of the general public. We use data from 18 days of interviews leading up to the 2016 election among 9,485 adults overall and 7,778 self-reported registered voters, with a median state sample size of 133.[2] Using this dataset, the models correctly predict the presidential winner in 50 of the 51 states and the District of Columbia, missing only Michigan, which was decided by 10,407 votes out of 4.8 million cast. The analysis estimates the national popular vote margin within four-tenths of a percentage point and produces lower errors on the Clinton-Trump margin across states than leading polling aggregators and non-probability 50-state polls.[3] We obtain similar results from analyses of ABC News and ABC/Post tracking data from the previous four presidential elections, demonstrating the robustness of the approach.

More than solely a predictive enterprise, the MRP analysis also sheds light on the dynamics of the 2016 race, in terms of trends over time and voting behavior among demographic groups. Except for the first four days of the tracking poll Oct. 20-23, the model found Trump ahead in the Electoral College even as he generally trailed Clinton in the popular vote. Notably, the narrowing of the race occurred prior to FBI Director James Comey's Oct. 28 letter to Congress reopening the controversy over Clinton's use of a private email server as secretary of

[1] The Post did not participate in the poll's first five days of interviews.
[2] The AAPOR response rate 3 for the full survey was 15.6 percent, including a cooperation rate (AAPOR 3) of 38.7 percent.
[3] We developed the model experimentally during the election; minor subsequent refinements included the use of more recent census data, elimination of a phone-status adjustment and addition of a time-trend adjustment. These changes had little effect. Our results were not publicly released prior to the election; as such we present this analysis solely as a proof of the utility of the approach, not as a claim to have made a public prediction.

state – an important analytical finding, given subsequent commentary blaming Clinton's loss on the Comey letter.

Our MRP analysis suggests that the electorate was older, slightly whiter and less well educated than suggested by the National Election Pool (NEP) national exit poll, and that Trump's victory among white voters was narrower than the exit poll suggests, with more-educated whites in particular more strongly for Clinton than in the exit poll. Given the exit poll's unadjusted or noisily adjusted group-level nonresponse, MRP likely provides a more accurate picture.

We proceed with the following sections: First, an overview of the motivation for MRP modeling and the statistical strategy employed for this analysis. Second, a description of the data used in the analysis. Third, turnout and candidate support estimates by state. Fourth, analysis of the race nationally and a discussion of group-level dynamics. Fifth, results of similar analyses using tracking poll data from the four previous presidential elections. Fifth, discussion of strengths and weaknesses of our approach, with suggestions for future research.

II. USING MRP FOR STATE-LEVEL ESTIMATES

Motivation

National-level surveys proved at least as accurate in 2016 as they have been in past elections – only slightly misstating the popular vote (overestimating Clinton's victory over Trump by 1-2 points), and more accurate on average than in 2012 (Silver 2017; Cohn, Katz and Quealy 2016). But state-level polling painted a different and ultimately much more inaccurate picture of the race. Trump prevailed in the Electoral College by narrowly winning primarily

Midwestern swing states where polling averages suggested that Clinton was ahead. Observers have pointed to a number of potential explanations for the large errors in state-level polling (Mercer, Deane and Kyley 2016). While disentangling these explanations is not the objective of this paper, the state poll misses do raise the specter of similar errors in the future.

MRP constitutes a promising alternative, avoiding uncertain rigor in state polls and the need for prescience in anticipating where to conduct them. Instead, MRP in this analysis relies on national-level survey data, in combination with statistical modeling and census data, to generate state-level estimates of voter turnout and candidate choice. The approach takes advantage of the fact that MRP can provide highly accurate state-level estimates of attitudes and behaviors even with relatively small number of observations in each state.

The statistical properties and substantive advantages of MRP have been discussed in detail elsewhere.[4] Researchers start with a national-level survey dataset, preferably with a fairly large number of observations. A multilevel statistical model predicting the outcome of interest is fit, using basic demographic variables that are available in census data at the state (or other subnational unit) level. Additional state-level variables can be included in the model in an effort to sharpen estimates. Coefficients for continuous variables usually are unmodeled (i.e., fixed), while group variables are modeled as categorical random effects. In the case of election-preference estimates, multiple models are required, first estimating the likelihood of voting, followed by additional model(s) estimating candidate preferences.

[4] See Park, Gelman and Bafumi (2004), Ghitza and Gelman (2013), Lax and Phillips (2009a, 2009b), Pacheco (2011) and Wang et al. (2014).

In the second stage of MRP analysis, the model estimates are used to predict the outcome variable for groups defined in a poststratification dataset. This dataset has an observation corresponding to each group defined for all combinations of the demographic variables included in the model. For example, if the model includes U.S. states/D.C. (n=51), gender (n=2) and a four-category race/ethnicity variable (n=4), the poststratification dataset will have 51*2*4= 408 rows, and will include the population size in each group from census estimates. After predicting the outcome variable for each of the groups in the poststratification dataset, estimates can be aggregated to the state (or other subgroup unit) level, with the subgroup population sizes determining the relative weight of each group's estimate in the state-level estimate.

MRP provides a powerful approach to generating state-level opinion estimates by pooling information from similar groups in other states, in effect leveraging subgroup-level attitudinal homogeneity (as established in regression analysis). Through multilevel modeling, results among multiple groups are partially pooled; for example, the prediction for Hispanic men living in Oregon will be informed by the outcome among similar Hispanic men in other states, other people living in Oregon, men across the country, Hispanics across the country, etc.

The degree to which estimates are partially pooled across groups is largely dependent on sample sizes; with larger samples, group estimates more closely reflect the outcome in the data, while estimates for smaller sample size groups are more dependent on the model (i.e., information provided by similar groups). Thus, pooling of data across states is particularly important for states with smaller sample sizes; estimates from states with larger sample sizes rely more on the survey data and less on the statistical model.

MRP is likely to prove most valuable relative to other approaches when particular features of the data hold true. First, MRP is most useful with moderately large national-level datasets – large enough to produce adequate state-level samples but not so large that those samples can stand alone. Second, moderate variation in the outcome variable across geographical subunits is desirable. If the outcome does not vary across states, classical regression would suffice; if the outcome varies greatly across states, partial pooling may be no better than disaggregation or classical regression (Gelman and Hill 2009, 247). Third, MRP works best when the demographic variables available for poststratification strongly predict the outcome; if they do not, estimates are likely to be poor (Lax and Phillips 2009b). In the case of modern American presidential elections, all three of these features hold true.

Statistical Strategy

As noted above, using MRP to predict election preferences by state requires estimating both propensity to vote, and candidate choice, among groups. In our analysis, starting first with candidate preferences, two sets of multilevel logistic regression models predicting preference for Clinton or Trump, respectively, were fit, with respondents preferring the other major-party candidate, a third-party candidate, or undecided set to 0.

The candidate preference equations are as follows:

$$\Pr\left(candidate_i^j\right) = \text{logit}^{-1}\big(\alpha_0 + \beta_1(2012\, party\ share) + \beta_2(black\ share) +$$
$$\beta_3(Hispanic\ share) + \beta_4(white\ evang.\ share) + \alpha_1^{gender} +$$
$$\alpha_2^{age5} + \alpha_3^{race4} + \alpha_4^{edu5} + \alpha_5^{state} + \alpha_6^{region} + \alpha_7^{age5,edu5} +$$

$$\alpha_8^{gender,edu5} + \alpha_9^{race5,age5} + \alpha_{10}^{race5,edu5} + \alpha_{11}^{race5,gender} +$$

$$\alpha_{12}^{race,region} + \alpha_{13}^{wave}) \quad (1)$$

In this equation, α_0 is the baseline intercept, while the remaining alpha coefficients correspond to variance components for the grouping variables, which include typical survey weighting variables (gender, age, education and race/ethnicity), geographical factors (state, region), and interactions between several of these factors (age*education, gender*education, race*age, race*education, race*gender and race*region). To capture any time trends, a random effect for time periods in the tracking survey ("waves") is included. The equation also includes three state-level variables and associated fixed beta coefficients suggested by previous research by others and testing with prior ABC/Post data to increase the precision of state-level estimates. These include the Obama and Romney vote shares in each state, respectively, (Ghitza and Gelman 2013; Wang et al. 2014) and the proportion of each state's population made up of African-Americans, Hispanics and evangelical white Protestants. The independent prior distributions for each of the varying coefficients are normally distributed with zero means and variances estimated from the data, $\alpha_j^S \sim \mathrm{N}\,(0, (\sigma^S)^2)$.

Best approaches for estimating group-level turnout likelihood are less clear. Group-level turnout has been estimated using data from other surveys related to the previous (or concurrent) presidential election. Wang et al. (2014) estimated group level turnout in 2012 using 2008 exit poll data, while others have employed the U.S. Census Bureau's Current Population Survey (CPS) voter supplement (Ghitza and Gelman 2013; Lauderdale 2016; Cohn and Cox 2016). These researchers justify this choice by pointing out that these sources measure reported turnout with probability-based sampling methods and large sample sizes, and argue that turnout rates by group do not vary substantially across elections.

Of course, if the assumption of constant subgroup turnout across elections does not hold, then these turnout estimates are likely to prove inaccurate. Given this consideration, we take an alternative approach, modeling turnout based on each survey respondent's self-expressed intention to vote and past reported voting participation. Specifically, respondents who said they were registered to vote at their current address, would definitely vote or had voted early and voted in 2012 were classified as voters (=1) while all other respondents were non-voters (=0). Of three operationalizations of turnout that were tested, this approach produced the most accurate estimates using previous years' data. Moreover, it should be noted that the goal was not to assemble literal voters but rather to predict the probability of turnout among groups, something this simplified approach accomplishes effectively. As a result, turnout is estimated with a nearly identical multilevel logistic regression model, with the difference being that the only state level variable included is the voting age population turnout in each state in 2012:

$$\Pr(vote_i) = \text{logit}^{-1}\big(\alpha_0 + \beta_1(2012\ \ VAP\ turnout) + \alpha_1^{gender} + \alpha_2^{age5} + \alpha_3^{race4} + \alpha_4^{edu5} + \alpha_5^{state} + \alpha_6^{region} + \alpha_7^{age5,edu5} + \alpha_8^{gender,edu5} + \alpha_9^{race5,age5} + \alpha_{10}^{race5,edu5} + \alpha_{11}^{race5,gender} + \alpha_{12}^{race,region} + \alpha_{13}^{wave}\big)$$

$$\alpha_j^S \sim \text{ N }(0, (\sigma^S)^2) \qquad (2)$$

In the next stage, the turnout model estimates were poststratified on the census dataset, producing an estimate of the number of Americans in each subgroup who were likely to vote. The preference model estimates (vote for Clinton, vote for Trump) next were poststratified on the estimated likely voter population in each subgroup. These estimates were adjusted to reflect time trends by using the final survey wave random effect estimate in the prediction, which essentially assumes uniform swings[5] in turnout/candidate preferences among groups. With these estimated numbers of voters overall and for each of the two main candidates, estimates of all three quantities could be aggregated to the state as well as subgroup levels.

III. DATA AND ESTIMATION

The national survey data chiefly used in the analysis is from the 2016 ABC News and ABC News/Washington Post tracking poll, a probability-based RDD cellular and landline telephone survey of respondents in the continental United States. We use data collected over 18 days preceding the Nov. 8, 2016, election, ending on Nov. 6. During each of the first 14 days, approximately 440 members of the general public were interviewed, while about 800 were interviewed per day on days 15-18, Thursday-Sunday before the election. A total of 9,485 respondents (including 7,778 self-reported registered voters) are included in the dataset, 65 percent of whom were interviewed via cell phone.[6] Figure 1 plots the sample size by state, ranging from six respondents in Alaska[7] to 1,084 in California, with the median state (Colorado) including 133 respondents.

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[5] The assumption of uniform swings may be a weakness of this approach, but consequential differential late-stage swings don't appear to be an issue, given the robustness of our model over time, and reliably testing time-trend interactions would require larger sample sizes than we have available.
[6] Additional methodological details are available at http://abcnews.go.com/US/PollVault/abc-news-polling-methodology-standards/story?id=145373.
[7] Respondents from Alaska and Hawaii only include those reached on cell phones with area codes from the continental United States.

As noted, for the turnout models, respondents were classified as voters if they (1) reported being registered to vote at their current address, (2) said they definitely would vote or already had voted and (3) said they voted in the 2012 election (*n*=6,193). Candidate preference questions were asked only of respondents who said they had voted or definitely would vote (*n*=6,825). Of these, those who said they preferred/voted for Clinton were coded as 1 for the Vote Clinton variable (*n*=3,073), with all others (supporters of Trump, third-party candidates and undecideds) coded as 0. Similarly, for the Vote Trump variable, Trump early voters and supporters were coded 1 (*n*=3,005) and all others 0.

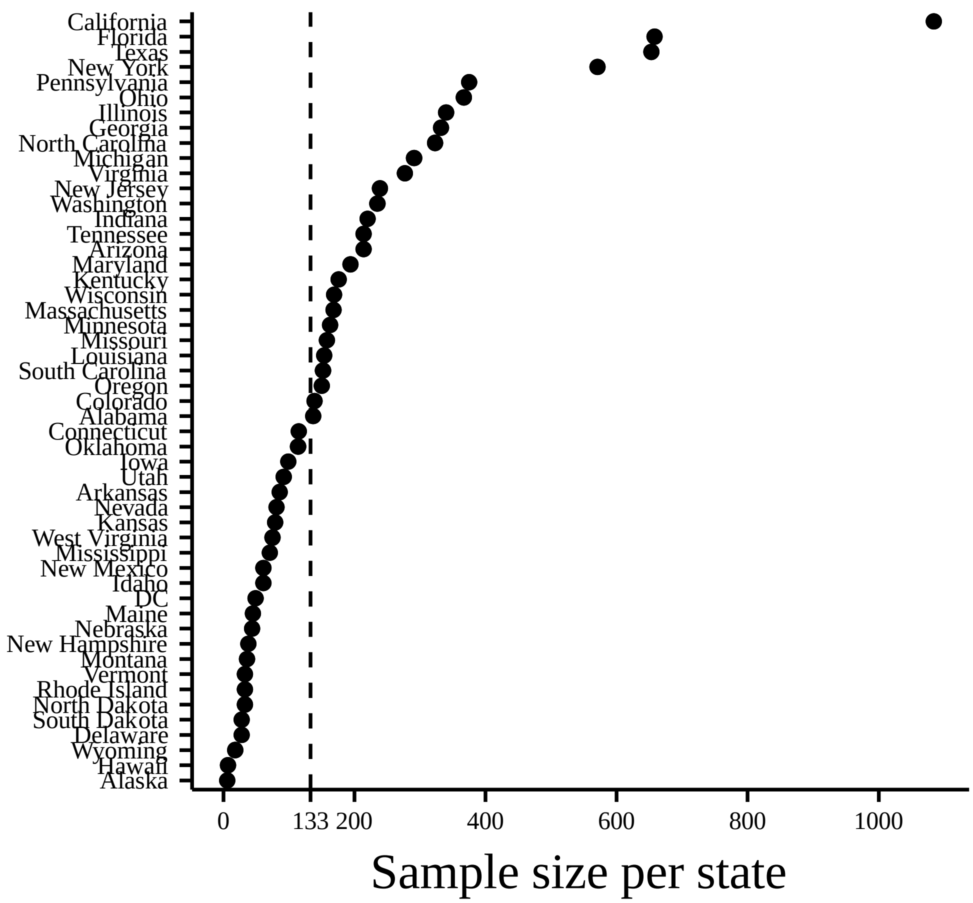

Figure 1. General population sample sizes per state. The dashed line indicates the median state sample size. MRP turnout models used this full sample, while candidate preference models were estimated among those who said they had voted or definitely would vote.

Demographic group variables included as random effects were gender (male, female), age (18-29, 30-39, 40-49, 50-64, 65+), race/ethnicity (white non-Hispanic, black non-Hispanic, Hispanic, and other non-Hispanic),[8] and education (less than high school, high school graduate, some college, four-year college graduate, post-graduate). State of residence was determined by area code and exchange for landline respondents and asked of cell phone respondents. The region variable used 13 sociopolitical regions based on state of residence. To capture any time trends, the tracking period was divided into five periods, the first three of which were four days in length and the last two at three days each.

Poststratification data were taken from the U.S. Census Bureau's 2015 American Community Survey (ACS) one-year estimates, the most recent census data released before the election. Since the poststratification dataset includes cells for every combination of the demographic variables included in the model, the dataset contains 10,200 rows with ACS estimates of the population size in each of these groups.

State-level variables included past voting-age-population turnout estimates compiled by McDonald (2016), prior vote shares for Obama and Romney in 2012, aggregate racial group shares from the 2015 ACS estimates and estimates of evangelical white Protestants in each state from the Public Religion Research Institute's American Values Atlas (2016).

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[8] Taking advantage of their larger sample size, the last four days of the tracking period included questions asking Hispanics whether they were born in the United States or abroad, for more fine-grained weighting. Models using the resulting five-point race/ethnicity variable produced similar results for this period.

For estimates of uncertainty, MRP models can be estimated with full Bayesian methods; this analyses uses a more approximate maximum likelihood estimator since the focus is on point estimates. Models were estimated in R using the glmer function in the lme4 package (Bates and Maechler 2009). After initial model runs, random effects with zero estimated variances were removed from the models to aid convergence.

IV. 2016 Results

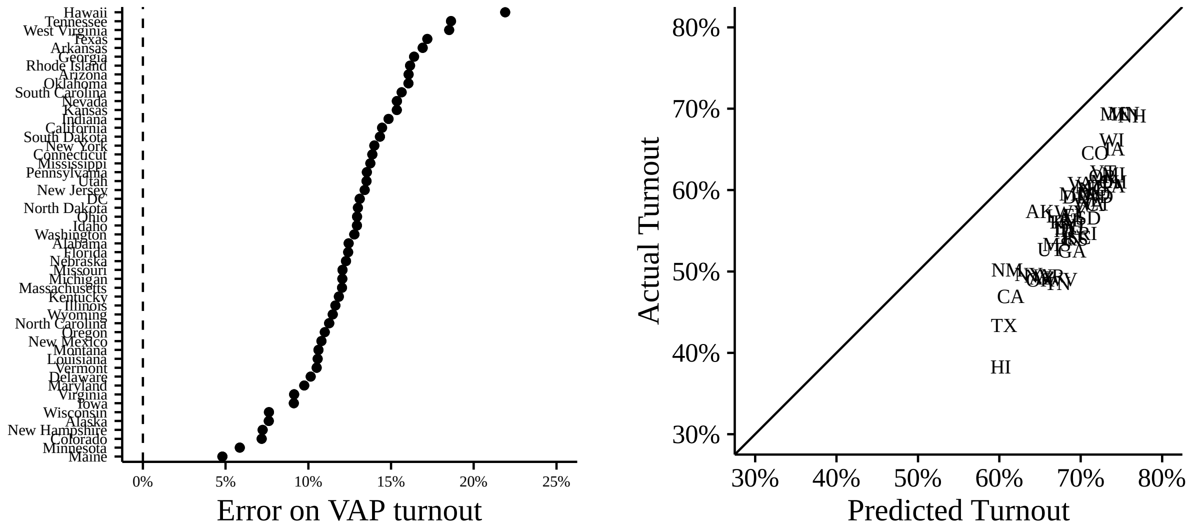
Turnout

The first step of the analysis is to estimate turnout by demographic group. Figure 2 shows the results of two turnout models using the 18-wave tracking dataset. (A table of estimates can be found in the Appendix.) The upper two graphs are based on models in which voters are classified as 1 if they said they had voted or definitely would vote, otherwise 0. The bottom two graphs report models in which the dependent variable is restricted only to include voters in the first model who also reported voting in the 2012 presidential election. For both models, the left-hand panels report the model error, that is, the difference between actual voting age population turnout (McDonald 2016) and the MRP predicted turnout by state.

Unsurprisingly, our comparatively simple MRP model significantly overpredicted VAP turnout. Although the VAP highest-office turnout reached 54.7 percent in 2016, the first, less-restrictive model estimated turnout at 67.8 percent and the more-restrictive model at 60.9 percent. The latter is much closer to turnout among the voting-eligible population (VEP, 60.2 percent), which excludes non-citizens, incarcerated citizens and those ineligible to vote due to criminal convictions, all groups that are likely to be undersampled in general population surveys.

Regardless, the predicted and actual turnout rates are highly correlated at the state level, with *r*=0.92 for the more restrictive model and *r*=0.91 for the less restrictive one, indicating their usefulness in predicting candidate support in the next step of the analysis.

MRP turnout predictions, using 'definitely will vote' as DV



MRP turnout predictions, 'definitely will vote' and voted 2012 as DV

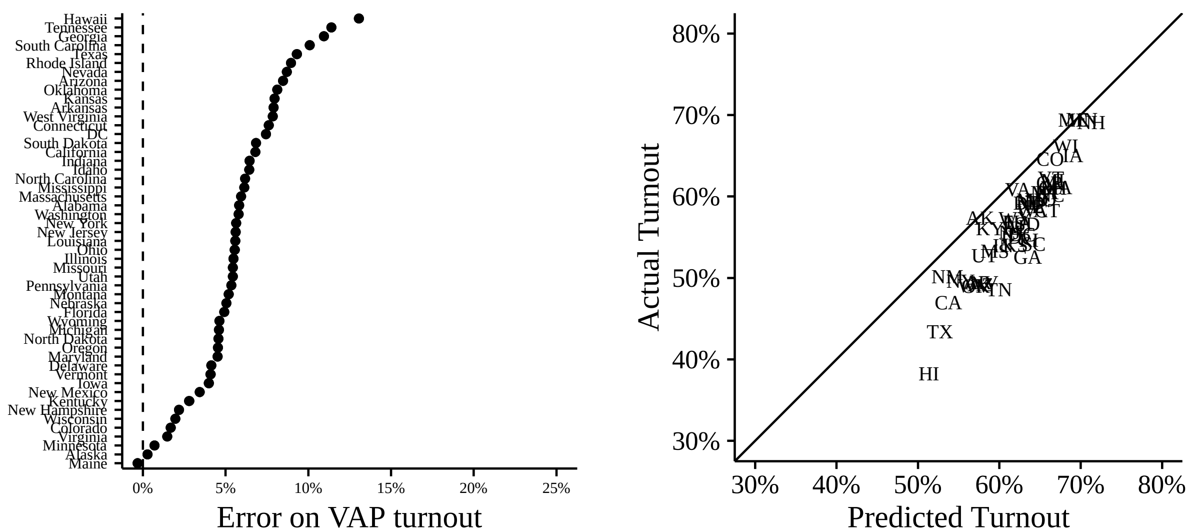


Figure 2. The top two panels plot the results of an MRP turnout model in which voters were defined as those who said they had voted or definitely would vote. The bottom two panels report the results of a second MRP turnout model in which voters also said they voted in the 2012 presidential election. The left

panels plot the model errors by state, with perfect predictions at zero and overpredictions as greater than zero. The right panels plot the MRP turnout predictions vs. the actual turnout. The models overestimated turnout in states below the 45-degree line; states for which turnout was overestimated would appear above the line.

The median absolute model error for the more-restrictive turnout model was 5.6 points. Errors reached double digits in a few states, with the largest for Hawaii at 13 points (a state not included in the sampling frame), followed by Tennessee (11 points) and Georgia (11 points). Turnout errors decreased as the level of actual turnout in each state increased; errors were minimal in high-turnout states such as Minnesota and Wisconsin. Indeed, the prediction error is correlated at $r = -0.77$ with actual turnout. This outcome may reflect a greater likelihood of voters to answer surveys. However, and important for estimates of national-level candidate support, turnout prediction errors were essentially uncorrelated with the Clinton-Trump candidate margins across states (r=0.01). The poststratified estimates of subgroup-level turnout from the restrictive model were used to identify the number of voters in each subgroup for the candidate-preference poststratification.

Vote Preference

The next set of models estimated preferences for Clinton (vs. other candidates) and Trump (vs. other candidates) using a similar set of demographic predictors at the individual level. To demonstrate the utility of including state-level predictors in the multilevel models, the first results in the top two panels of Figure 3 are based on models that did not include any state-level predictors, while the bottom two panels are based on models that also included 2012 vote shares for Obama and Romney and the proportions of blacks, Hispanics and evangelical white Protestants in each state's population. Coefficient estimates are given in Appendix A.

While the MRP estimates for both sets of models were not perfect at the state level, overall they proved quite accurate. Clinton won the national popular vote by 2.1 points (48.2 to 46.1 percent); the estimates from the MRP models reported in Figure 2 show 2.2- and 2.5-point Clinton leads, respectively (46.7 to 44.4 percent and 46.8 to 44.3 percent). The models also proved highly accurate in predicting which candidate would win in each state and fairly accurate in predicting those vote margins. The first set of models correctly predicted 45 of 51 races (and a narrow electoral-college victory for Clinton, 275-263). Adding 2012 vote shares (not shown) increased the number of correct predictions to 47, while the models including aggregate racial/ethnic shares missed only Michigan, the state with the closest margin.

For all states, the root mean square error (RMSE) on the Clinton-Trump margin for the second set of models is 5.8 points, dropping to 4.5 points after excluding Hawaii, Alaska and the District of Columbia. The RMSE for the Clinton and Trump estimates per state for the full model are 2.3 and 3.5 points (excluding Alaska, Hawaii and D.C.), respectively, indicating quite accurate point estimates for each candidate. The absolute errors on the Clinton-Trump margins only reach double digits in three low-population states (Hawaii, North Dakota and Wyoming) and D.C., while eight state margin estimates are off by 5-10 points (Alaska, Louisiana, Mississippi, New Mexico, Oklahoma, Rhode Island, South Dakota, and West Virginia).

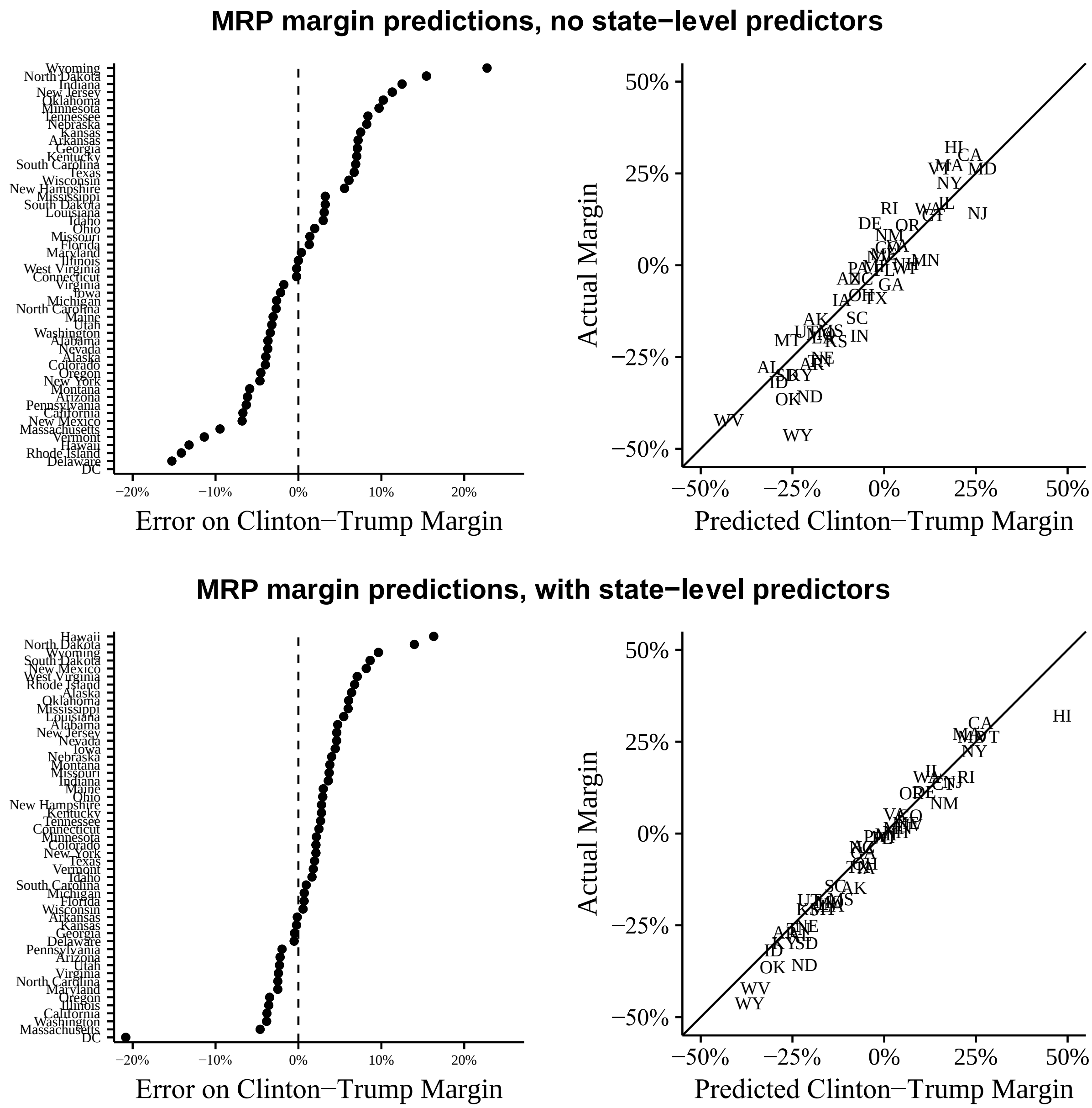


Figure 3. The top two panels plot the results of MRP candidate-preference models predicting support for Clinton or Trump in each state with models that did not include state-level variables. The bottom two panels report the results of a second set of MRP candidate-preference models including state-level predictors. The left panels plot the model errors on the Clinton-Trump margin by state, with perfect predictions at zero, overprediction for Clinton to the right of zero and overprediction for Trump to the left of zero. The right panels plot the MRP Clinton-Trump margin predictions vs. the actual state-level margins. Overestimates of Clinton's margin over Trump are below the 45-degree line and underestimates of Clinton's margin over Trump are above the line.

Notably, the MRP estimates are particularly accurate in swing states, with the RMSE on the Clinton-Trump margin at only 2.5 points, proving more accurate in the states that mattered most in deciding the election outcome and where state polling aggregates were most likely to miss. Table 1 reports the predicted and actual margins in swing states along with margin errors and polling averages from Huffpost Pollster for comparison. The MRP estimate came within 1 point of the actual Clinton-Trump margin in Georgia, Wisconsin, Florida and Michigan; from 2 to 3 points in Pennsylvania, Colorado, Minnesota, Arizona, Virginia, North Carolina, New Hampshire and Ohio; and 4 to 5 points in Iowa and Nevada. While the polling averages were particularly poor in Midwestern swing states with high numbers of less-educated whites, in only Iowa and Ohio was MRP off by 3 points or more on the margin in Clinton's favor. The model was slightly too pro-Trump in Pennsylvania. MRP's absolute errors on the margin were smaller than the polling average errors in all the swing states except Colorado, Arizona, Virginia, and Nevada, where the polling averages tended to do slightly better.

		Huffpost Pollster		**MRP Estimates**		
State	**Actual**	**Average**	**Error**	**Predicted**	**Error**	**State N**
Georgia	-5.2	-2.4	2.8	-5.6	-0.4	332
Wisconsin	-0.8	6.1	6.9	-0.2	0.6	169
Florida	-1.2	1.8	3.0	-0.5	0.7	658
Michigan	-0.2	6.0	6.2	0.5	0.7	291
Pennsylvania	-0.7	4.1	4.8	-2.7	-2.0	375
Colorado	4.9	4.9	0.0	7.0	2.1	139
Minnesota	1.5	6.9	5.4	3.7	2.2	163
Arizona	-3.5	-1.6	1.9	-5.8	-2.2	214
Virginia	5.3	5.3	0.0	2.9	-2.4	277
North Carolina	-3.7	1.6	5.3	-6.1	-2.5	323
New Hampshire	0.4	3.3	2.9	3.2	2.8	38
Ohio	-8.1	-1.0	7.1	-5.2	2.9	367
Iowa	-9.4	-3.0	6.4	-5.0	4.4	99
Nevada	2.4	2.1	-0.3	7.0	4.6	81

Table 1. Actual Clinton-Trump margins vs. the Huffpollster polling average and MRP estimates in swing states.

Comparison to Aggregators

While MRP's accuracy is impressive, given the closeness of the election in many states and the RMSEs of the estimates, missing only one state likely was due to chance. However, as shown in Table 2, our MRP model results outperform the predictions of polling aggregators as well a sophisticated MRP model that employed a large non-probability online dataset. This is true not only in terms of the number of states correctly predicted but also in the accuracy of state-level point estimates.

As noted, our MRP model correctly predicted 50 of 51 contests, vs. 46 correct predictions for the leading aggregators, 45 for The New York Times' Upshot and 43 for SurveyMonkey and YouGov's MRP model.[9] Similarly, the RMSE on the Clinton-Trump margin for our MRP model is 5.8 points for all states, dropping to 4.5 points after excluding Alaska, Hawaii and D.C. and 2.5 points among battlegrounds. In the comparison models, the RMSE exceeds 7 points for all states, with no or only marginal improvement when excluding Alaska, Hawaii and D.C.[10] Our MRP model's RMSE among battleground states also outperforms the comparison models, with the closest being Fivethirtyeight, with a 3.9-point RMSE for these states (vs. our 2.5). Our

[9] Note that the number of correct predictions assumes that the predicted winner in each state is the one with the higher predicted vote share in that state. Some of the forecasted total electoral vote shares differed for the aggregator models (e.g., Fivethirtyeight) because electoral votes were simulated separately. These alternative models also produced estimates for states that allocated electoral votes by congressional district (Maine and Nebraska), which our MRP model was not designed to accommodate.
[10] The improvements in our MRP estimates for these contests reflect the fact that Alaska and Hawaii were not in the sample frame, while D.C. is an unusual case with few respondents.

MRP's greater accuracy also holds when examining the two-party margin RMSE as well as the estimates for each major-party candidate.

	Our MRP	538	HuffPo	DKos	YouGov MRP	Survey Monkey	NYT Upshot
Clinton %	46.8%	48.5%	45.7%	NA	47.9%	NA	NA
Trump %	44.3%	44.9%	40.8%	NA	44.1%	NA	NA
Margin	2.5 pts.	3.6 pts.	4.9 pts.	NA	3.8 pts.	NA	NA
Correct predictions	50	46	46	46	43	43	45
RMSE margin all	5.8%	7.1%	7.1%	7.0%	7.6%	7.6%	7.0%
RMSE margin no AK, HI, DC	4.5%	6.7%	7.2%	7.0%	7.6%	7.6%	7.0%
RMSE margin battlegrounds	2.5%	3.9%	4.5%	4.7%	5.5%	5.5%	4.9%
RMSE 2 party margin (no AK, HI, DC)	4.6%	7.1%	7.1%	6.9%	8.0%	8.0%	NA
RMSE Clinton % (no AK, HI, DC)	2.3%	3.1%	3.6%	2.7%	3.3%	3.3%	NA
RMSE Trump % (no AK, HI, DC)	3.5%	4.0%	6.9%	6.6%	4.7%	4.7%	NA

Table 2. Our MRP prediction estimates and RMSEs compared with others.

In particular, our model's strength comes more from its substantially higher accuracy in estimating Trump's vote share. The RMSE for our Clinton estimates is 2.3 points, compared with 2.7 to 3.6 points for the comparison estimates. The difference is larger on average for the Trump estimates, with the RMSE for MRP at 3.5 points, vs. comparison model RMSEs ranging from 4 to 6.9 points.[11]

[11] Figures in the table are based on available data. Beyond these estimates, several aggregators published probabilistic projections of the election results, with final estimates of a 71 percent probability of a Clinton victory by FiveThirtyEight, 85 percent by The New York Times Upshot, 92 percent by the Daily Kos, 98 percent by The Huffington Post and greater than 99 percent by the Princeton Election Consortium.

Time Trends

Our MRP model predictions suggest that aside from a larger Clinton lead in the popular vote in the first four days of the tracking period (Oct. 20-23), the race was quite close, with Clinton generally ahead in the popular vote but Trump leading in the Electoral College. Figure 4 plots estimated Clinton-Trump vote shares at the national level using two approaches. The left-hand panel presents results from a single set of models using the full tracking data adjusted for the random effect predictions for each three- to four-day period included. This approach essentially assumes uniform swings across groups by period for turnout and candidate preferences. The right-hand panel presents the results from MRP models run on data from each wave separately, allowing the importance of different demographic variables to vary with each wave. The disadvantage of this approach is the smaller sample sizes for each of the separate models, which likely lead to less stable estimates.

MRP candidate predictions across tracking, uniform swing vs. separate models by period

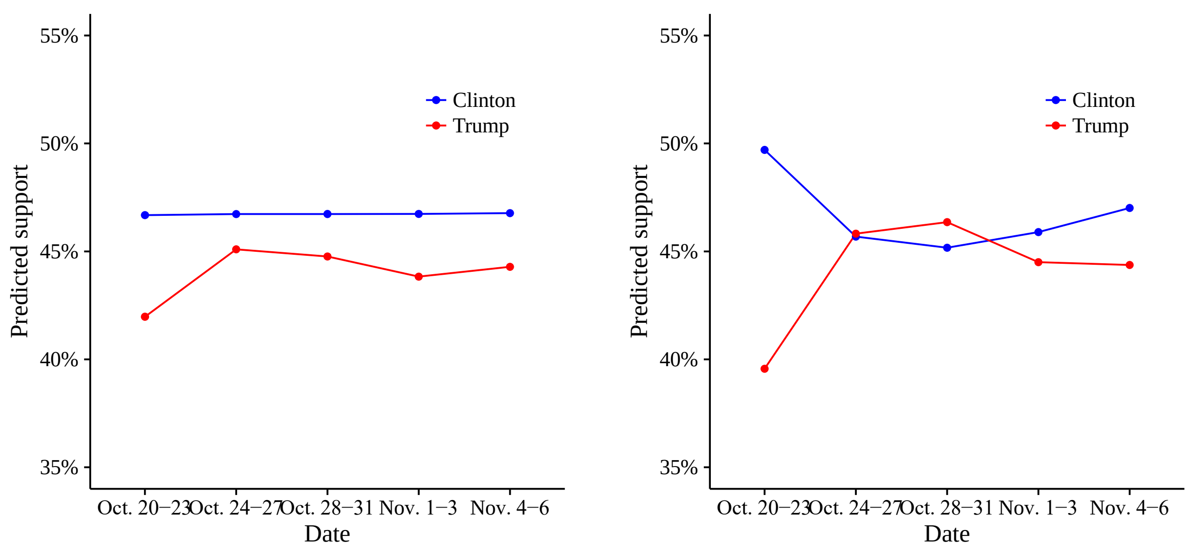


Figure 4. MRP candidate support predictions across the tracking period. The left panel predictions ("uniform swing") are based on a single model including all of the tracking data with random effects for each period. The right panel reports predictions for separate models for each period.

Both approaches suggest a large Clinton lead during the first four days, by five points according to the "uniform swing" model and 10 points for the separate modeling approach. In both cases, Clinton is predicted to win the Electoral College, though not overwhelmingly in the uniform swing model (288-250). For both methods, the race narrows substantially after these first four days, which followed the third presidential debate and a period in which Trump underwent heavy criticism, including defections by GOP leaders, after the release of a videotape in which he was heard crudely describing sexual advances toward a woman. Though Clinton retained the support of about 46.7 percent of voters throughout the full course of tracking according to the uniform swing approach, Trump came as close as 45.1 percent in the second period (Oct. 24-27). In the separate modeling approach, Trump's support exceeded Clinton's from Oct. 24-Oct. 31. With both approaches, Trump led Clinton in predicted Electoral College votes during every period beyond the first four days. Notably, the narrowing of the contest at the national level, and the flip in the Electoral College prediction, occurred prior to FBI Director James Comey's Oct. 28 letter to Congress about a renewal of the agency's investigation into Clinton's email server.[12]

[12] If the first four days are excluded from the analysis, MRP correctly predicts all 51 contests and RMSEs are further reduced.

Subgroup Estimates

In terms of turnout, the subgroup-level variables that proved most predictive are education, age, and (at some distance) race (see Table A1, column 2 in the Appendix). Variance in turnout also is explained, but to lesser extents, by gender and state, and as well as by a number of interactions between race and the other demographic variables. As far as fixed effects, the VAP turnout in the respondent's state in 2012 is highly predictive; while positive, the coefficient associated with living in a battleground state does not reach conventional statistical significance. Overall, these findings are consistent with research linking age and socioeconomic status with turnout.

The variables that matter most for candidate preferences differ somewhat, but also provide a clear picture of election dynamics (see Table A2, columns 3 and 6). Variance in support for both Clinton and Trump is best explained by race/ethnicity, followed by gender, race by education, race by gender and education on its own. Age is less important; it does not explain support for Clinton and its impact on support for Trump is relatively minor compared with other variables. Higher support for Clinton and lower support for Trump among younger generations is more a function of higher levels of education and greater nonwhite shares among younger Americans.

In terms of the fixed effects, Obama and Romney vote shares in the respondents' states are highly predictive, as is the proportion of each state's residents who are African-American, with higher shares related to lower support for Clinton and higher support for Trump, reflecting the greater GOP lean of whites in states with higher percentages of African-American residents. There's a similar pattern for the Hispanic share of residents, though this variable only reaches marginal levels of significance in the Trump support model. The influence of evangelical white Protestants does not reach statistical significance in either model, though it just misses marginal significance in positively predicting support for Trump.

To clarify the consequences of these patterns in turnout and support, it is possible to use the poststratification dataset to generate subgroup level predictions of these outcomes. In doing so, MRP provides a somewhat different story of the election dynamics than those portrayed by the NEP national exit poll, differing most substantially by age group and whites by education.

Table 3 compares MRP national estimates for subgroup-level turnout, turnout share and candidate preferences with estimates from the national exit poll. In terms of turnout share, MRP and the exit poll estimate the exact same shares of men and women (47-53 percent). By contrast, our MRP analysis estimates turnout share among 18- to 29-year-olds at 11 percent, vs. 19 percent according to the exit poll, and MRP estimates seniors at 25 percent of voters, compared with 16 percent in the exit poll. MRP also suggests that the electorate was much less well educated; 63 percent of voters did not have a college degree according to our analysis, compared with only half according to the exit poll. MRP puts the share of whites at 73 percent, compared with 71 percent in the exit poll, with the 2-point difference coming equally from blacks and Hispanics. Finally, differences emerge among whites by gender and education (degree vs. no degree); while these four groups made up nearly equal shares of the electorate according to the exit poll, whites without a college degree (both men and women) were a larger share of the electorate according to our MRP analysis. The older, whiter and less well-educated electorate from our MRP analysis is consistent with previous CPS-based estimates (Cohn 2016).

	MRP Estimates	**NEP Exit Poll Estimates**

Subgroup	Turnout	Turnout share	Clinton	Trump	Margin	Turnout share	Clinton	Trump	Margin
Male	58%	47%	40%	50%	-10 pts.	47%	41%	52%	-11 pts.
Female	63	53	52	40	12	53	54	41	13
18-29	31	11	49	34	15	19	55	36	19
30-39	55	16	50	36	14	17	51	39	12
40-49	66	18	48	45	3	19	46	49	-3
50-64	73	31	46	47	-1	30	44	52	-8
65+	78	25	44	51	-7	16	45	52	-7
No degree NET	54	63	42	49	-7	50	44	51	-7
HS or less	44	30	43	50	-7	18	46	51	-5
Some college	66	34	42	48	-6	32	43	51	-8
Degree NET	79	37	54	36	18	50	52	42	10
College	78	23	50	40	10	32	49	44	5
Postgraduate	82	14	61	31	30	18	58	37	21
Whites	69	73	38	54	-16	71	37	57	-20
Nonwhites NET	46	27	71	19	52	29	74	21	53
Blacks	57	11	87	6	81	12	89	8	81
Hispanics	36	9	63	28	35	11	66	28	38
Among whites									
Men no deg.	60	21	25	66	-41	16	23	71	-48
Women no deg.	65	24	35	58	-23	17	34	61	-27
Men deg.	83	14	43	46	-3	17	39	53	-14
Women deg.	83	14	55	37	18	20	51	44	7

Table 3. MRP subgroup estimates of turnout, turnout share and candidate preferences compared with NEP national exit poll estimates.

These turnout differences also are associated with somewhat different candidate preference estimates for these groups.[13] Most important, we find greater polarization in the vote by education, both overall and among whites only. Our MRP analysis finds that Clinton won

[13] These patterns hold if they are calculated based only on the two-party vote share within each group.

college graduates by 18 points, vs. only 10 points in the exit poll. Among whites, Trump won both men and women without a college degree by slightly narrower margins according to MRP relative to the exit poll, while Clinton pulled nearly evenly among white men with a college degree (-3 vs. -14 Clinton-Trump) and was far ahead among white women with a college degree (+18 vs. +7).

Put together, the exit poll suggests that whites were somewhat more pro-Trump than MRP finds, going for the Republican candidate by 20 points, vs. by 16 points according to MRP. Clinton's margin of victory among blacks and Hispanics is similar in both approaches. Notably, MRP suggests that Clinton won Hispanics by 35 points, close to the exit poll's 38 points but lower than some have argued using other data sources (Sanchez and Barreto 2016).

Our MRP estimates may be more accurate than the exit poll, which resorts to observation-based adjustments to differential nonresponse by gender, race and age; weights otherwise simply are used to align the data with actual vote results. Previous analyses have suggested that these non-response adjustments are insufficient to compensate for higher exit poll cooperation rates among more educated and younger voters (McDonald 2007; Cohn 2016). This can lead to implausible estimates for turnout, particularly half of the electorate having college degrees when only about three in 10 Americans have them. By forcing the data to "add up," the exit poll likely underestimated Clinton's support among whites with college degrees and slightly overestimated Trump's support among less-educated whites.

V. PAST ELECTIONS

To assess the accuracy of the MRP approach across time, we conducted similar analyses using ABC/Post tracking surveys for the 2000, 2004, 2008, and 2012 elections.[14] While the analyses differed slightly in the state-level variables[15] included and the demographic interactions that proved most predictive, the analyses essentially followed the methods described for the 2016 election.

Table 4 summarizes the results for the last five presidential elections. On average, MRP correctly predicts 48 of 51 contests; it misses the Electoral College and popular vote winner only in the 2000 election. The average RMSE on the Democratic-Republican candidate margins across elections in all 51 contests is 6.7 points, falling to 5.7 points when Alaska, Hawaii and D.C. are excluded. For candidate percentages, the RMSE is 2.9-3.4 points on average, excluding the idiosyncratic contests (Alaska, Hawaii and D.C.).

MRP correctly estimates an essentially tied race in 2000, but reverses the popular vote and Electoral College winners. MRP slightly overestimates Obama in the popular vote and Electoral College in 2008, while underestimating his Electoral College victory in 2012. The 2004 MRP slightly underestimates Bush's popular vote and Electoral College victories. The 2012 and 2016 models are the most accurate, both in terms of correct state predictions and RMSE, with 2012 having the smallest errors. The greater accuracy of MRP in the last two elections may

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[14] The 2000 and 2004 tracking polls included more sample days and more respondents per day than the latter tracking polls. For a clearer comparison, for these two elections a more limited number of tracking days were analyzed to make for comparable sample sizes across elections.
[15] For example, estimates of the proportion of evangelical white Protestants in each state were not available for the first three elections.

reflect increasing shares of early voters (McDonald (2016) and greater predictive power of the included demographic variables for these elections.[16] Sharpening the 2000-2012 models to take greater account of contest-specific dynamics may make them more accurate still.

	2000	2004	2008	2012	2016	Average
Democrat %	46.9%	47.6%	54.6%	51.0%	46.8%	
Republican %	47.2%	48.7%	42.7%	46.2%	44.3%	
Margin	-0.2%	-1.0%	12.0%	4.8%	2.5%	
Pred. Dem. Evs	276	242	372	285	249	
Pred. Rep. Evs	261	295	166	253	289	
Correct predictions	47	48	47	49	50	48.2
RMSE margin all	8.2%	6.7%	8.2%	4.6%	5.8%	6.7%
RMSE margin (no AK,HI,DC)	6.6%	5.6%	7.3%	4.5%	4.5%	5.7%
RMSE margin battlegrounds	3.9%	4.0%	5.5%	3.2%	2.5%	3.8%
RMSE Dem. % (no AK, HI, DC)	3.4%	3.2%	3.4%	2.3%	2.3%	2.9%
RMSE Rep. % (no AK, HI, DC)	3.8%	3.1%	4.0%	2.4%	3.5%	3.4%

Table 4. Summary of MRP estimates from prior elections. Prior MRP models differed slightly in terms of the state-level predictors included, and some included cross-level interactions. Models were estimated on comparable Ns; for 2008 and 2012, this included the full tracking data, while for 2000 and 2004 the models were estimated on a subset of tracking data, given their larger samples and longer durations.

VI. Discussion

While higher-quality polling in swing states likely would have improved predictions in the 2016 election, MRP provides an attractive alternative. As this paper demonstrates, even with relatively small state-level sample sizes, our MRP approach substantially outperforms leading

[16] Indeed, income, rather than education, is probably a better predictor of voting behavior in the earlier elections (Gelman et al. 2007). Improved polling methodology may also be a factor, as more recent elections have included cell phone interviews and interviews conducted in Spanish.

polling aggregators in the 2016 election, and analyses of previous elections indicate the robustness of the technique.

This performance is likely related to factors including the quality of the underlying data and attributes specific to our approach. First, by using a single national-level survey, our MRP estimates are based on data collected with the same methods across states, while state-level surveys averaged by aggregators vary widely in methods and quality. To the extent that lower-quality or poorly devised polling methods produce inaccurate estimates, the presumed canceling-out benefits of aggregation can lead to biased and misleading results. Second, and relatedly, the analysis reported here is based on one of the most methodologically sound probability-based RDD surveys of its type in the country (Silver 2016). These data may present advantages over non-probability data or voter registration lists; the latter suffer from sizable noncoverage and noisy weighting variables.

MRP also offers an alternative to traditional survey weighting and likely voter modeling that overcomes some of the challenges faced by standard survey weighting techniques (Gelman 2007) – either iterative proportional fitting, which does not guarantee precise subgroup sizes, or cell weighting, which can be compromised by limited sample sizes. MRP is analogous in many ways to cell weighting, without the troubles associated with zero- or small-n cells. In the analysis presented here, the model estimates were poststratified on 10,200 cells, essentially a much finer-grained weighting scheme than either rake or typical cell weighting.

Though it presents significant advantages, MRP is not a cure-all for challenges facing pollsters. The greatest restriction is that MRP does not provide a single weight that can be used for all variables in a survey; instead it requires each outcome of interest to be modeled separately.

In another limitation, the relative accuracy of the approach in predicting recent state- and national-level election outcomes is strongly related to the degree to which demographic variables available for poststratification predict voting behavior. While such demographic variables have been highly predictive in the past several elections, the future is unknown. To ensure continued accuracy, researchers employing the technique need to adjust the demographic and state-level predictors included in the model to the dynamics of any given election, based on exploratory data analysis and other prior information.

Future research may lead to additional improvements in the accuracy of the MRP approach employed here. Other strategies for estimating turnout (e.g., other deterministic operationalizations, continuous turnout variables or CPS-based models) could enhance subgroup-level turnout estimates. Future research also could examine whether and how to poststratify on variables such as partisan identification or past vote (Wang et al. 2014; YouGov 2016), albeit with an eye to the inherent risks of doing so. Finally, the analysis could be conducted using full Bayesian methods, which would facilitate the calculation of uncertainty for the estimates.

For all its utility, MRP, in the application presented here, can only take us so far in understanding the dynamics of an election. While, as we demonstrate, MRP can produce precise state- and group-level turnout and candidate support predictions, it can only hint at how different groups come to their choices. In this sense, MRP cannot replace more probing questions on voters' pre-political dispositions, policy preferences and views of candidate attributes that form the substance of voter decision making. That said, we recognize the intense media and public interest in discerning the likely winner of elections before they are held. If such predictions are to remain a dominant element of our pre-election landscape, it is best that they be accurate.

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APPENDIX A: STATISTICAL TABLES

Table A1: Predicting voter turnout, multilevel logistic regressions

	Definite voter	Definite voter & voted in 2012
Fixed part (β)		
Intercept	0.05	-0.63
	(0.62)	(0.72)
VAP vote 2012	0.91	1.46**
	(0.58)	(0.62)
Battleground	0.10	0.08
	(0.08)	(0.09)
Random part (σ)		
Gender	0.12	0.12
Age	0.67	0.88
Race	0.38	0.38
Education	0.89	1.02
State	0.08	0.12
Region		
AgeXedu	0.13	0.12
GenderXedu		
RaceXage	0.18	0.14
RaceXedu	0.12	0.06
RaceXgender	0.09	0.08
RaceXregion	0.13	0.10
Survey wave	0.09	0.12
AIC	8857.5	9153.5
N	9024	9024

**p<0.01 *p<0.05 (fixed part)

Estimates are from multilevel logistic regressions predicting voter turnout using waves 1-18 of the 2016 ABC News and ABC News/Washington Post election tracking poll. The dependent variable for the first column is equal to 1 if the respondent is registered to vote and said s/he definitely would vote or had already voted, otherwise 0. The dependent variable in the second model is the same as the first except voters (1) also said they voted in the 2012 presidential election. The fixed part reports unstandardized beta coefficients along with standard errors, while the random part reports the estimated standard deviations of the random effects. Random effects with zero estimated variances were removed from the models.

Table A2: Predicting voter support for Clinton and Trump, multilevel logistic regressions

	Support Clinton			Support Trump		
	M1a	**M2a**	**M3a**	**M1b**	**M2b**	**M3b**
Fixed part (β)						
Intercept	0.51	-1.25	-1.03	-1.26	-3.03**	-3.4**
	(0.59)	(0.65)	(0.71)	(0.78)	(0.82)	(0.82)
Obama 2012 %		3.51**	3.69**			
		(0.57)	(0.59)			
Romney 2012 %					3.71**	3.37**
					(0.60)	(0.56)
Black %			-1.99**			2.20**
			(0.38)			(0.39)
Hispanic %			-0.10			0.72†
			(0.38)			(0.39)
White evang. Prot. %			-0.12			0.90
			(0.60)			(0.59)
Random part (σ)						
Gender	0.43	0.43	0.44	0.55	0.55	0.56
Age				0.28	0.28	0.28
Race	0.96	0.95	0.99	1.26	1.24	1.29
Education	0.19	0.18	0.18	0.22	0.21	0.21
State	0.28	0.16	0.05	0.29	0.18	0.05
Region	0.20			0.26		
AgeXedu				0.09	0.09	0.08
GenderXedu						
RaceXage	0.08	0.07	0.08			
RaceXedu	0.30	0.30	0.30	0.34	0.34	0.34
RaceXgender	0.15	0.15	0.15	0.39	0.39	0.39
RaceXregion	0.25	0.19		0.22	0.18	
Survey wave				0.09	0.08	0.08
AIC	7821.7	7795.1	7782.3	7686	7657.4	7498.1
N	6376	6376	6376	6376	6376	6376

**p<0.01 *p<0.05 †p<0.10 (fixed part)

Estimates are from multilevel logistic regressions predicting preferences for Clinton or Trump, respectively, among those who said they had already voted or definitely would vote using the 2016 ABC News and ABC News/Washington Post election tracking poll. The fixed part reports unstandardized beta coefficients along with standard errors, while the random part reports the estimated standard deviations of the random effects. Random effects with zero estimated variances were removed from the models.