Decoupling and Contrasting Turnout and Sentiment in Electoral Change: Evidence from recent Congressional Elections

Tobias Konitzer*[1], Sharad Goel†[1], David Rothschild‡[2], and Houshmand Shirani-Mehr§[1]

[1]Stanford University

[2]Microsoft Research

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1 Introduction

In 2010, the Republican surge in the Congressional elections was dubbed the "Tea Party takeover" in both, academic research (Karpowitz et al., 2011; Jacobson, 2011),

*tobiask@stanford.edu
†scgoel@stanford.edu
‡davidmr@microsoft.com
§hshirani@stanford.edu

and journalism (CNN, 2011). "An energized conservative electorate, fueled by the anti-establishment Tea Party movement that emerged in 2009, helped Republicans to what could be their biggest gain in congressional elections in decades," proclaimed CNN (2011). A large share of voters indicated that "they supported the Tea Party movement", wrote Jacobson (2011) in the *The New York Times.* What's less clear is how exactly the Tea Party affected the 2010 midterms. There is two scenarios, both widely reported: In one, voters, upset with a declining economy, issued a referendum on the Obama administration, changed their minds and turned toward the Republican candidates riding the Tea Party coattails (Jacobson, 2011; Zeleny, 2010). In another, the Tea Party wave had mobilized an electorate substantially more Republican in their party orientation, and more conservative than had been the case in the past several midterms (Saad, 2010; Burmila, 2014; Silver, 2011).

In the literature, electoral change from presidential to Congressional elections has been discussed either through the surge and decline paradigm that establishes differing turnout as a main driver of electoral change (especially Campbell, 1987, 1960; DeNardo, 1980; Martinez and Gill, 2005), or through the referendum theory, that establishes short-term forces such as presidential approval as a driver of change, thus implying some level of sentiment change (Tufte, 1978, 2006). Yet, studies have focused on one disconnected from, or ignoring, the other, and we are not aware of any study providing a complete decoupling, and then contrasting, of the impact on electoral change. In this paper, we develop an taxonomy of determinants of electoral change – turnout composition and sentiment change. We derive a mathematical expression for both, turnout and sentiment change and show that change in any election can be exhaustively explained by these determinants, both conceptually and mathematically. In a second step, we show that such a structural decoupling of electoral change is important in interpreting election results in applying our structural approach to decoupling electoral change to the 2010 and 2014 Republican surge in the House respectively.

Methodologically, our contribution lies in a serious advancement of Model-Based Post-Stratification (MP) (see for example Park, Gelman and Bafumi, 2004; Gelman et al., 2016; Ghitza and Gelman, 2013). Our structural approach of decoupling electoral change relies on developing accurate aggregated estimates of vote choice for granular sub-demographics. While MP is a useful tool for this task (Park, Gelman and Bafumi, 2004; Ghitza and Gelman, 2013), we advance the MP literature by developing a Competition-based Method of Post-Stratification (CMP), which chooses the least error-prone method from an array of off-the-shelf Machine Learning algorithms, shrinkage models, and Bayesian multilevel linear Models, instead of exclusively relying on the standard of MP in the literature up until now, multilevel modeling (Park, Gelman and Bafumi, 2004; Gelman et al., 2016; Ghitza and Gelman, 2013).

In concluding, we discuss repercussions of our structural decoupling of electoral change for both, journalists and researchers. We note that the previous status quo – looking at exit-polls – has lead to misattributions of change. Specifically, we debunk the narrative that young people have tilted Republican in the 2010 and 2014 elections. In addition, we note that decoupling of turnout and sentiment change also has repercussions for predicting election outcomes. We show that a purely ex ante approach of our method is able to predict election outcomes more accurately than so-called fundamental models for all Congressional elections that we consider here, 2008, 2010, 2012, and 2014, but especially for elections in which fundamental models failed by all accounts – 2010 and 2014 (Lewis-Beck and Tien, 2010; Abramowitz, 2010; Hibbs, N.d.; Brady, Fiorina and Wilkins, 2011). When it comes to methods, we discuss the potential of CMP to increase accuracy in MP applications, especially in those not related to voting. In all, this study is the first we are aware of that structurally and rigorously decouples electoral change, relying on Big Data and advanced statistical analytics.

2 Decoupling Electoral Change

We start with the simple assumption that electoral change can be exhaustively explained by sentiment change – voters changing their minds – and turnout change – changes in the composition of the turnout population. Consider a simple scenario: In one district (District A) in Election 1, half of the voting population are men and the other half are women. The Republican vote share is 60% among men and 40% among women. As the result, the Republican vote share in Election 1 is 50%. Two years later, the composition of the voting population is still the same, yet the general opinion among male voters has swung towards the Republican candidate. This time, 65% of men and 40% of women vote for the Republican candidate, and the final vote share of the Republican candidate in Election 2 is 52.5%. We call the difference of 2.5 percentage points electoral change. It is easy to see that in this fictitious example, electoral change can be completely accounted for by sentiment change – voters changing their vote choice from Election 1 to Election 2.

Now let's consider a different example. In District B, the composition of the voting population and the sentiment among the voters is the same as in District A in Election 1. Two years later, the opinion of that population is still the same, yet this time the voting population consists of 60% men and 40% women. Subsequently, the Republican vote share in Election 2 is 52%. But this time the 2 percentage points electoral change is entirely accounted for by changes in the composition of the turnout population.

One last example shall illustrate that turnout and sentiment change can exhaustively account for electoral change. District C has the same sentiment and turnout composition as the other two districts in Election 1. Two years later, the voting population consists of 60% men and 40% women, and sentiment among the voters has changed such that the Republican vote share is 65% among men and 40% among women. The Republican vote share in Election 2 is 55%. This time electoral change was brought about by a mix of changes in the composition of the turnout population and sentiment change.

Mathematically, we begin with an expression for sentiment change, $\triangle V_s$. For convenience, suppose that sentiment change captures the degree to which sentiment has become more Republican from Election 1 to Election 2. If we knew exactly how the voting population in Election 1 would have voted in Election 2, the difference between this counterfactual estimate and the actual outcome of Election 1 captures sentiment change. In other words, we hold the electorate constant, and are interested in *sentiment changes* amongst that electorates. We can write

$$\triangle V_s = M_{1\to 2} - V_1 \tag{1}$$

where $M_{1\to 2}$ is the hypothetical Republican vote share among the voting population of Election 1 in Election 2, and V_1 is the actual Republican vote share in Election 1. Going back to our examples in the beginning of this section, using this notation we document a sentiment change of 2.5 percentage points for District A, zero percentage points for District B, and 2.5 percentage points for District C.

We can likewise write down an expression for changes in turnout, $\triangle V_t$. For convenience, suppose that $\triangle V_t$ captures proportional increases of Republican-leaning constituencies among the electorate, e.g. relative increases in white, male voters who identify as Republican. Again, if we knew exactly how the voting population in Election 1 voted in Election 2, the difference between this counterfactual estimate and the actual outcome of Election 2 captures changes in the composition of the turnout population. In other words, we hold the sentiment constant, and are interested in *changes in the turnout population.* We can write

$$\triangle V_t = V_2 - M_{1\to 2} \tag{2}$$

In our examples, we document a turnout change of zero percentage points for District A, 2 percentage points for District B, and 2.5 percentage points for District C.[1]

[1]Note that the change in District C is the combination of changes in District A (pure sentiment change) and District B (pure turnout change), yet electoral change in District C outweighs the sum of changes in District A and District B. In our decomposition, we define sentiment change as the electoral change from Election 1 to Election 2, if only sentiment changed, and assign the

Conceptually, we have decomposed electoral change exhaustively. This is also true mathematically. Adding the quantities above yields

$$\begin{aligned} \triangle V_t + \triangle V_s &= V_2 - M_{1\to 2} + M_{1\to 2} - V_1 \\ &= V_2 - V_1 \end{aligned} \tag{3}$$

which is indeed the complete electoral change between both elections.

It is easy to see how determinants of electoral change in Congressional elections discussed in the literature fit into our taxonomy. Redistricting, for example (Gelman and King, 1994; Abramowitz, Alexander and Gunning, 2006), yields changes in the electorate, and would be included in $\triangle V_t$. Incumbency advantage (Abramowitz, Alexander and Gunning, 2006; Abramowitz, 1991; Gelman and King, 1990; Maisel and Stone, 1997) falls under turnout change $\triangle V_t$ if the incumbent motivates a different set of voters to turn out, and under sentiment change $\triangle V_s$ if the presence of an incumbent *sways* voters who usually turn out. Macro-level changes, on the other hand, amongst them religious and political sorting, migration and immigration (Muste, 2014; Abramowitz, Alexander and Gunning, 2006; Bishop and Cushing, 2008), lead to changes in the electorate, and falls under $\triangle V_t$.

rest of electoral change to turnout change. In consequence, sentiment changes in District C and District A are equal in our fictitious example. Alternatively, we could define turnout change as the difference of the actual outcome of Election 1 and the counterfacual estimate of how the voting population in Election 2 voted in Election 1. Now, turnout change in District C would be equal to turnout change in District B in our fictitious example. However, in this decomposition we will have a small interactive effect of turnout and sentiment change, which explains the difference between the combined effect and the sum of individual effects outlined above. In our current decoupling, we include this small interactive effect under turnout change. Alternatively, we can assign it to sentiment change. Neither of these strategies fundamentally changes the results.

It is also clear that this taxonomy is an important one. Interpretations of election outcomes become wildly different if it is found that actual voters changed their vote choice, as supposed to a different set of voters turning out to vote. For example, as we address more below, analyses that indicate a conservative shift of young voters in both, 2010 and 2014 are mistaken (e.g Bacon Jr., 2010).

3 Data and Methods

To decompose electoral change between Election 1 and Election 2 into sentiment and turnout components, we need to estimate the hypothetical Republican vote share of voters from Election 1 in Election 2 ($M_{1\rightarrow 2}$). Specifically, to study electorate changes in 2010 and 2014 elections, we need to estimate $M_{2008\rightarrow 2010}$ and $M_{2012\rightarrow 2014}$.

For sentiment by demographics we utilize the Cooperative Congressional Election Study core surveys 2008, 2010, 2012, and 2014, which provide a very large national sample of voters with unusually large district samples. The precise sample sizes used for our analyses were 19,337 for 2008, 41,913 for 2010, 36,413 for 2012, and 31,688 for 2014.

To estimate this hypothetical vote share, we rely on Modeling and Post-Stratification (MP). Specifically, we first model the sentiment in the survey data based on demographics information using different machine learning algorithms. We train a variety of classifiers, including logistic regression, Bayesian multilevel regression, random forest and elastic net, on a training set in each year, with sample size 15,470 for 2008, 33,531 for 2010, 29,131 for 2012, 25,351 for 2014. We then choose the best model based on performance on a holdout test set, with sample sizes 3,867 for 2008, 8,382 for 2010, 7,282 for 2012, 6,337 for 2014. We derive the probabilities of voting Republican for granular subdemographics based on the best-performing model, and weight these probabilities based on the proportion of that demographic in the desired target population.

For the Bayesian hierarchical linear model, we fit

$$\begin{aligned}
\mu_i^{\text{voter}} &= \beta_{\text{sex}} \times \text{sex}[i] + \beta^{\text{race}}_{\text{race}[i]} + \beta^{\text{age}}_{\text{age}[i]} + \beta^{\text{education}}_{\text{education}[i]} + \beta^{\text{party}}_{\text{party}[i]} \\
&+ \beta^{\text{age:gender}}_{\text{age:gender}[i]} + \beta^{\text{age:education}}_{\text{age:education}[i]} + \beta^{\text{age:party}}_{\text{age:party}[i]} + \beta^{\text{age:race}}_{\text{age:race}[i]} \\
&+ \beta^{\text{gender:education}}_{\text{gender:education}[i]} + \beta^{\text{gender:party}}_{\text{gender:party}[i]} + \beta^{\text{gender:race}}_{\text{gender:race}[i]} \\
&+ \beta^{\text{education:party}}_{\text{education:party}[i]} + \beta^{\text{education:race}}_{\text{education:race}[i]} \\
&+ \beta^{\text{party:race}}_{\text{party:race}[i]} \\
\mu_i^{\text{district}} &= \beta^{\text{district}}_{\text{district}[i]} + \beta^{\text{division}}_{\text{division}[i]} \\
&+ \beta^{\text{previous vote}} \times \text{previous vote}[\text{district}[i]] \\
&+ \beta^{\text{division:age}}_{\text{division:age}[i]} + \beta^{\text{division:gender}}_{\text{division:gender}[i]} + \beta^{\text{division:edu}}_{\text{division:edu}[i]} + \beta^{\text{division:party}}_{\text{division:party}[i]} \\
g(\Pr(y_i = \text{Republican})) &\sim \text{Bernoulli}(\mu_i^{\text{voter}} + \mu_i^{\text{district}})
\end{aligned} \tag{4}$$

Note that g indicates the logit function, β^{foo} indicate random effect coefficients, and β_0 is a non-random intercept. Further note that all regression coefficients are assigned a hierarchical normal prior with mean 0 and separate variance parameters. The variance parameters are all drawn from truncated (half-) Cauchy distributions (Gelman, 2006).[2]

For logistic regression, we fit the exact same model as above, but obviously no

[2]We fit the model via Stan, using 4 chains and 1,000 iterations each, which yields appropriate convergence statistics.

partial variance pooling, or Bayesian smoothing, occurs. We also implement a regularized version of logistic regression model using elastic nets with following regularization term:

$$\lambda \sum_{j=1}^{p} (\alpha \beta_j^2 + (1-\alpha)|\beta_j|) \tag{5}$$

where α and λ are tuning parameters, and are selected by cross-validation on our training set using 10-fold cross-validation. Finally, we fit a random forest classifier as a non-linear model to the data, given that random forests constitute the set of most accurate off-the-shelf machine learning algorithms (Hastie, Tibshirani and Friedman, 2009). We compare models by computing simple accuracy, or binary correctness on the holdout test set.

To derive M, we fit the winning model of CMP again on the whole survey data (training and test sets combined), and compute the probability of voting Republican for each of the demographic categories defined by our model. We then weight all probability estimates of voting Republican according to the proportion of that synthetic voter type (i.e. demographic combination) in the turnout population (Park, Gelman and Bafumi, 2004). Specifically, we calibrate our model for $M_{2008 \to 2010}$ on the survey data from 2010, and weight it according to the 2008 population. For $M_{2012 \to 2014}$, we calibrate our model on the survey data from 2014, and weight it according to the 2012 population. If we were interested in national-level estimates, we could simply sum over all weighted estimates, but MP allows for studying electorate changes at granular subdemographic levels. For example, we can decompose the electoral change across age-groups by computing $M_{2008\to2010}$, V_{2008}, and V_{2010} for each age-group separately. We can simply write

$$M^{(\text{age-group})}_{2008\to2010} = \frac{\sum_{j\in\text{age-group}} N_j\pi_j}{\sum_{j\in\text{age-group}} N_j} \tag{6}$$

where the sum is over all demographic combinations in the population, while N_j and π_j are the number of voters and the predicted Republican vote-share in demographic combination j. $V^{(\text{age-group})}$ for each year is simply derived by weighting our sub-group estimates in that year by the fraction of the respective subgroups that turned out to vote in that year.[3]

For our turnout population, we draw the numbers of registered voters from a proprietary voter file, *VoterBase*, collected by *Target Smart*. *VoterBase* is a national voter file that contains information on over 191,000,000 registered voters: Records from state and county election authorities are augmented with consumer data on household level demographics, lifestyle, and interest data.[4]

Because the decennial redistricting took place in 2012, but we only have voter

[3]In this particular case, we can compute $V^{(\text{age-group})}$ using exit polls as well. However, computing the election outcome using our subgroup estimates gives us the ability of studying the sentiment and turnout decomposition for the granular subdemographics for which we do not have data from exit polls. Additionally, for subgroups that are studied in exit polls, we estimates closely match the election outcomes.

[4]We derive a partisan identity using a proprietary imputation model developed by TargetSmart. This imputation is based on hundreds of thousands of aggregated interviews from national surveys on party self-identification based on demographic, consumer, census and other synthetic variables. The end result is a weighted probability of identifying as a Democrat assigned to each individual. We impute a Democratic partisan identity to individuals who have a likelihood of identifying Democratic of .8 or higher and a Republican partisan identity to individuals who have a likelihood of identifying Democratic of .2 or lower. Changes in this cut-off do not substantively change our results. While it is problematic to use a static measure of party ID taken from our 2016 data, we note that 1) party ID has been found to be extremely stale (Donald Philip Green, 1994; Converse, 1969), and 2) our results do not change if we leave party id out of our MP models.

file data from 2016, we have to make some slight modifications to derive $M_{2008\rightarrow2010}$, V_{2010} and V_{2008}. Specifically, we assign a district to each of the voters by empirically drawing from the full list of districts their zip-codes could have been a part of. For decoupling electoral change from 2012-2014, i.e. for deriving $M_{2012\rightarrow2014}$, V_{2014} and V_{2012}, we do not have to deal with redistricting.

We could get estimates of turnout and sentiment change from a combination of stand-alone survey data and exit polls. This approach, however, comes with serious shortcomings in decomposing electoral change for granular subgroups. First, neither survey data nor exit polls are amenable to deriving subgroup estimates due to high variance, but MP does not face this problem. Second, survey data suffer from systematic errors in self-reported turnout, but the voter files used in our approach fully and accurately represents the turnout population.

Because we later compare district-level predictions of Republican vote share for 2008, 2010, 2012, and 2014 to generic fundamental models, we also briefly describe fundamental models used here. The first set of independent variables in our models are past vote shares in the district for the house and presidential elections. The second set of variables pertain to incumbency, i.e. what party won the seat in the previous election and whether that incumbent was running in the cycle in question. Specifically, the outcome variable for district i is the Democratic two-party vote share (V_{Di}) - 0.5. The first independent variable is the Democratic two-party vote share in the district for the previous election (${V_D^{(t-1)}}_i$). The second independent variable is the average presidential vote share in the district for the last two cycles - average presidential vote share for those same two cycles

($\triangle_i \bar{V}_P$). The third independent variable is a dummy if the Republican party won the last election and the seat is open (I_i[Rep Victory, Seat Open]). The fourth independent variable is a dummy if the Democratic party won the last election and the seat is open (I_i[Dem Victory, Seat Open]). The fifth independent variable is a dummy if the Democratic party won the last election and the Democrat is running (I_i[Dem Victory, Dem Running]). We predict for the years 2008, 2010, 2012, and 2014. While we predict 2012, we do not use it in the calibration, because redistricting from the 2010 Census makes it unreliable.

$$\begin{aligned} V_{Di} = \alpha + \beta_1 \, {V_D^{(t-1)}}_i + \beta_2 \, \triangle_i \bar{V}_P + \beta_3 \, I_i[\text{Rep Victory, Seat Open}] \\ + \beta_4 \, I_i[\text{Dem Victory, Seat Open}] + \beta_5 \, I_i[\text{Dem Victory, Dem Running}] \end{aligned} \tag{7}$$

4 Results

We begin by displaying the results of CMP for all years 2008, 2010, 2012 and 2014. Elastic Net outperforms Bayesian hierarchical models (HLM) and our other MP models in all years. While the poor performance of HLM might be surprising, we note that the advantage of Bayesian smoothing might be lost in a setting in which the predictor space is, at least theoretically, very well defined: directional vote (e.g Markus and Converse, 1979).

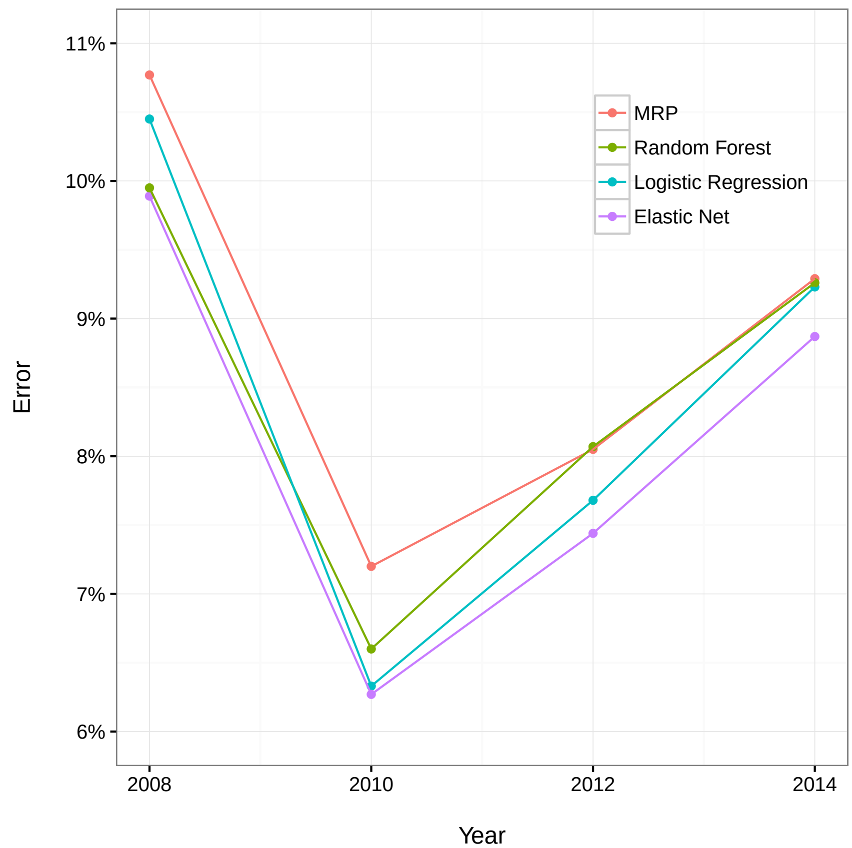

Figure 1: CMP Errors of 4 different MP Models

We proceed by showing the estimated electoral change plotted against the estimated change in sentiment for various subdemographics. First, we discuss changes from 2008-2010. It is obvious that our measure of sentiment change accounts for our measure of electoral change to differing degrees. If we consider age, for example, while 19-29 year old have turned Republican from 2008 to 2010, our measure of sentiment change actually indicates a slight tilt toward the Democratic party among that age group. In other words, the move toward the Republican party among that age group can be entirely accounted for by a different set of 18-29 year olds (i.e.

more Republican leaning) turning out to vote, and not by actual persuasion of the same voters.

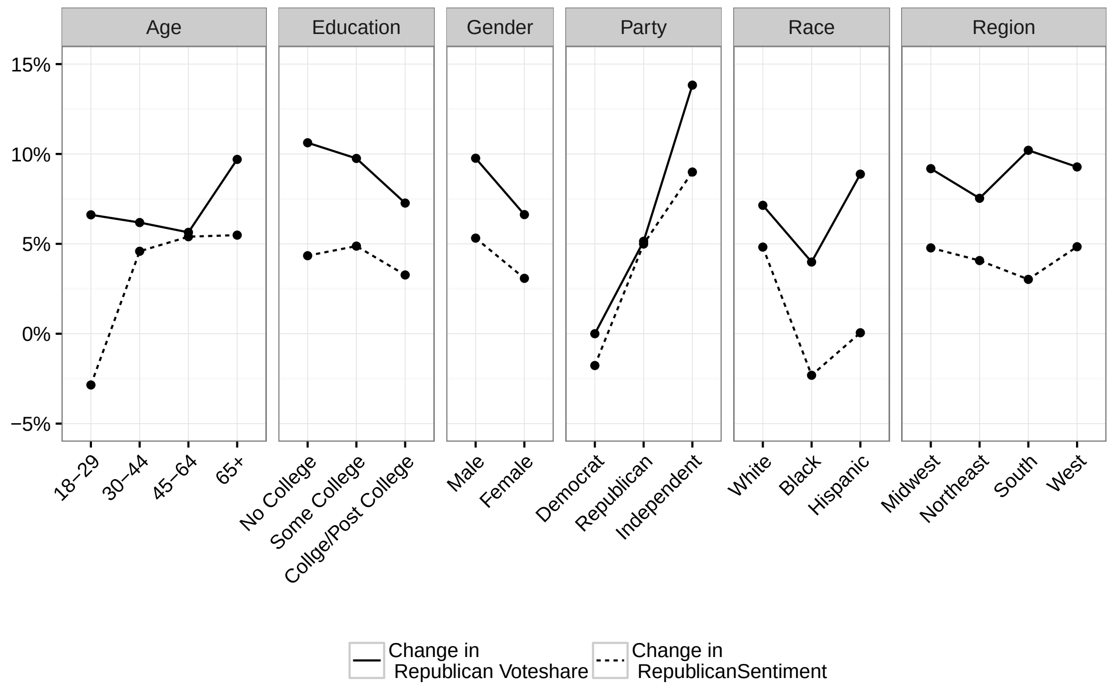

Figure 2: Estimated sentiment change plotted against electoral change from 2008 to 2010

If we look at differing levels of education, we find that sentiment change actually accounts for a good portion of overall electoral change. For example, while the vote share of the demographic of non-college educated voters has become more Republican by about ten percentage points, roughly half of that change is accounted for by actual sentiment change. This pattern is repeated in the breakdown by gender. While the Republican vote share of men has gone up by about ten percentage points from 2008 to 2010, our method indicates that roughly half of this can be accounted for by a different set of men turning out to vote – in light of the journalistic narrative of the Tea Party takeover,[5] it is certainly sensible to assume that most of the electoral change among this demographic should be attributed to a different set of men turning out to vote in 2010 than in 2008, and not to sentiment change.

Reassuringly, when we break down voters by party, most of the electoral change that we register for Republicans and Democrats is changes in sentiment – it would be conceptually troubling to document that it was shifts in the composition of Republicans or Democrats that triggered electoral change amongst that group. For independents, most of the electoral change is actually accounted for by sentiment change, which makes sense given what we know about the persuadability of independents (Zaller, 1992). Race offers an interesting pattern: While white sentiment has moved Republican by 5 percentage points, the bulk of the overall electoral change of that group, movements to the right by Hispanics and Blacks are primarily a function of different Blacks and Hispanics turning out, rather than sentiment change among these groups. Last, when we look at regions, we find a more or less idiosyncratic pattern, with roughly half of the electoral change being a function of sentiment change, and half being a function of changes in the composition of the turnout population.

When we look at electoral change 2012-2014, we first note that electoral change was much smaller, i.e. the Republican surge was much less pronounced than 2008-2010. Akin to our previous discussion, we first break down the decoupling of electoral change by age demographics. Again, we find virtually no sentiment change among 18-29 year olds. In fact, most of the electoral change among different age groups

[5] See for example http://www.cnn.com/2010/POLITICS/11/02/election.main/.

can be entirely explained by a different kind of population turning out to vote in 2014 compared to 2012. The notable exception is 65 year olds and older, who have shifted their sentiment toward the Republican party. In fact, we estimate that the 2.5 percentage point increase in Republican vote share among this demographic can be almost entirely explained by shifts in sentiment.

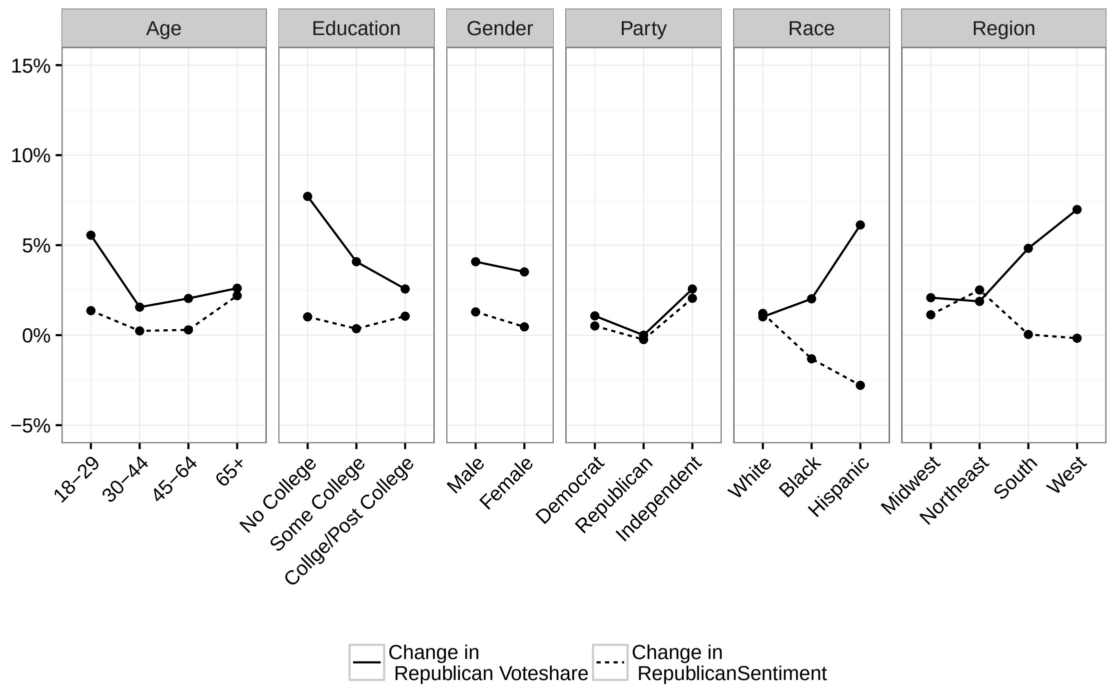

Figure 3: Estimated sentiment change plotted against electoral change from 2012 to 2014

Next, we decouple electoral change for different education levels. We find that the bulk of electoral change among non-college educated and those with some college education can be accounted for by differences in the composition of the turnout population. On the other hand, roughly half of the movement of college educated voters toward the Republican party can be accounted for by shifts in actual sentiment. Broken down into gender, we find that the majority of electoral change can be accounted for by changes in the turnout population. Again, we further find that independents' shift in vote is primarily a function of persuasion. Looking at race, we find a similar pattern as in 2008-2010. The move of white voters toward the Republican party – although small in magnitude – is mostly accounted for by sentiment change, while moves toward the Republican party by Blacks and Hispanics are primarily a function of a different set of Blacks and Hispanics turning out to vote. In fact, we find that Hispanic and Black sentiment has become slightly *more* Democratic. Finally, we consider the decoupling of electoral change in different regions. In the Midwest and the Southeast, most of the Republican gain can be explained by changes in actual sentiment. In the South and West regions, however, we find that differences in turnout populations have been driving electoral change primarily.

Next, we display the importance of such a structural decoupling, looking at a specific example from our 2008-2010 analysis. As we noted before, exit poll estimates are usually taken as indications of sentiment change, but this might lead to serious misattributions. For example, exit polls registered a 7 percentage point swing of 18-29 year olds toward the Republican party from 2008 to 2010,[6] but our model suggests that sentiment change among this demographic was virtually non-existent. How can that be? According to the previous discussion of electoral change, this inevitably has to mean that a different set of 18-29 year olds turned out in 2010 compared to 2008, and that is exactly what we find.

[6]see http://www.cnn.com/ELECTION/2008/results/polls.main/ for 2008 exit polls and http://www.rickweil.com/Elections/2010/ExitPoll2010.htm for 2010 exit polls.

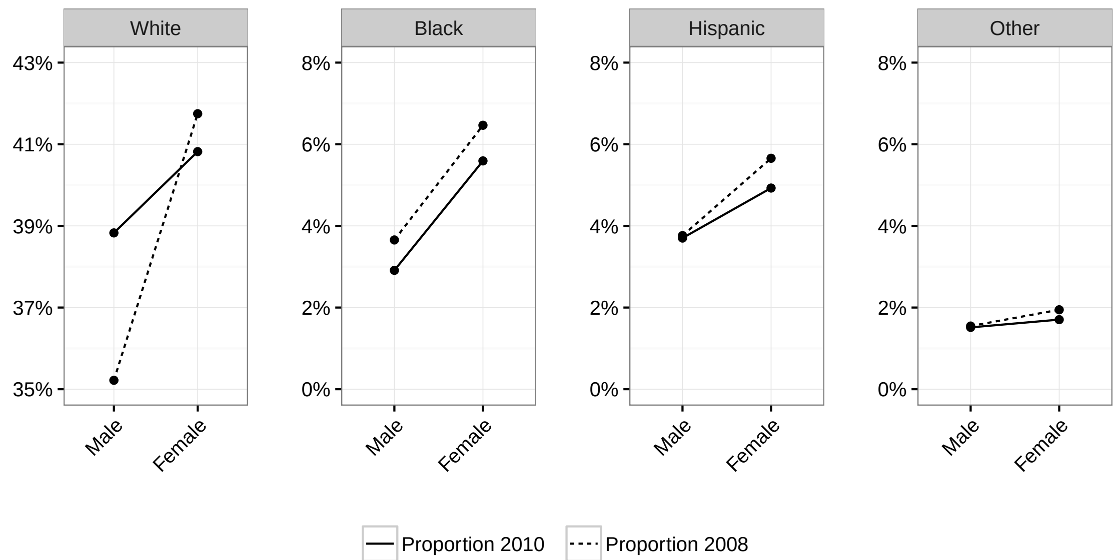

Figure 4: Composition of 18-29 year olds who turned out to vote in 2008 and 2010

Figure 4 displays the known demographic breakdown of those 18-29 year olds who turned out to vote in 2008 and 2010 respectively. It is quite clear that indeed, a different set of 19-29 year olds turned out in the two elections. In 2010, over 40% of the turnout population of that demographic was male, compared with around 38% in 2008 for example. In general, we show that those demographics who turned out more frequently in 2010 than in 2008 were leaning much more Republican, supporting our finding that differences in vote among the demographic of 18-29 year olds can mainly be explained by changes in turnout, not in sentiment (Figure 5).

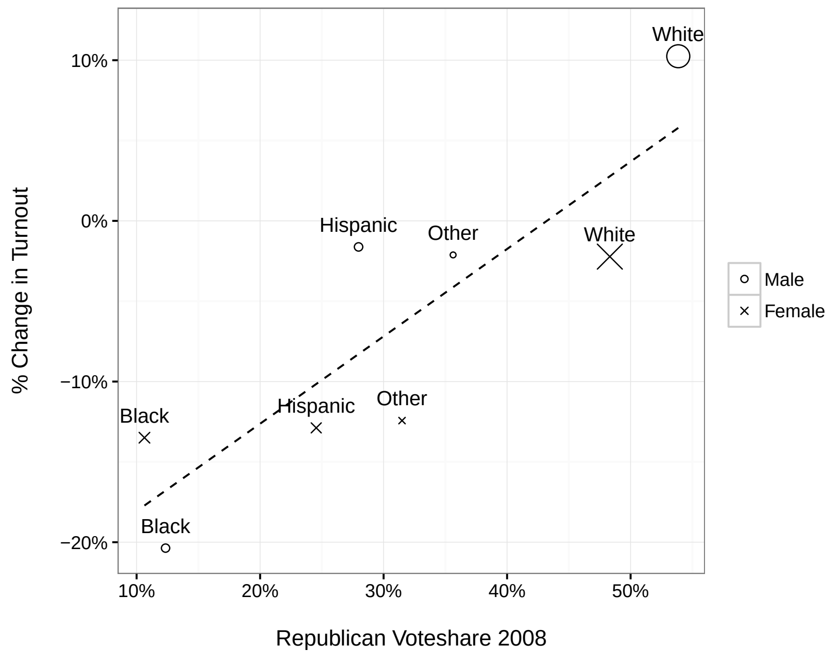

Figure 5: Estimated Republican vote share of demographics that experienced a surge in turnout from 2008-2010; dots plotted proportional to size of demographic

Finally, we show that such a decoupling of electoral change has also repercussions for accurately predicting election outcomes. Fundamental models try to capture both, changes in the composition of the electorate and changes in sentiment. For example, a "midterm"-dummy, capturing the difference in turnout population in on and off-election years is routinely included in many House election models (Lewis-Beck and Tien, 2010; Abramowitz, 2010), and an incumbency indicator, capturing both sentiment and turnout change also contributes a sizable amount in explained variance (Abramowitz, 2010). However, pure prediction models relying on such contextual and institutional factors and no granular estimate of sentiment change, such as the Hibbs model (Hibbs, N.d.), vastly under-predicted the Republican surge in

2010. The fact that models including national-level variables able to capture national mood change, such as presidential approval ratings (Lewis-Beck and Tien, 2010), did relatively little to lower model error is further evidence for the importance of predicting turnout *and* sentiment accurately. In consequence, models that take into consideration decoupling turnout and sentiment change should do better in predicting election outcomes.

To illustrate, we construe district-level estimates of Republican vote share for 2008, 2010, 2012 and 2014 from our MP models. To derive true predictions, we rely on the estimated turnout population based on who turned out 4 years prior. In effect, these models could be run truly ex ante, as soon as survey data on prospective vote choice is available. In Figure 7, we indeed show that our survey-based MP model outperforms in predicting election outcomes against the fundamental models in all years. In 2008, the mean absolute error for our ex-ante model is 4.93, vs. 5.35 in the fundamental model. In 2010, the differences are more pronounced. The mean absolute error for our ex-ante model is 4.57, vs. 8.58 in the fundamental model. In 2012, the mean absolute error for our ex-ante model is 3.71, vs. 5.79 in the fundamental model. Finally, in 2014, the mean absolute error for our ex-ante model is 3.91, vs. 4.08 in the fundamental model.

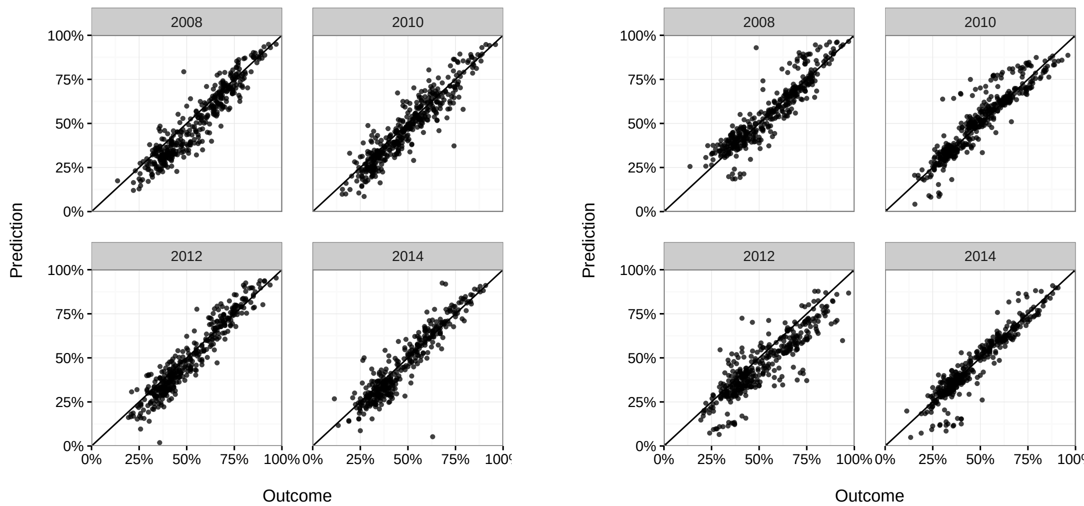

Figure 6: MP prediction of House elections (left); Fundamental model predictions of House elections (right)

5 Conclusion

In this paper, we develop an exhaustive taxonomy of electoral change. We decompose electoral change into two elements – sentiment change and turnout change. We show that MP models with deep interactions are able to decouple sentiment change from changes in the turnout composition in ways that exit polls or simple survey analyses cannot. Specifically, we show that for different demographics, the Republican surges of 2010 and 2014 are functions of sentiment change and changes in the composition of the turnout population in ways that popular and academic commentary has previously been unable to quantify.

Furthermore, we show that such a decoupling of turnout and sentiment change is of consequence for both, predicting and interpreting elections. For example, the narrative of decline of Democratic support amongst young voters is, in light of this analysis, almost entirely artifactual (e.g Bacon Jr., 2010). In short, it matters to researchers, journalists and campaign staffers alike whether people change their minds or their willingness to turn out. Future research would do well in investigating drivers of turnout change and sentiment change, their similarities, and their differences.

The compelling interest in this line of research was made obvious in the aftermath of the 2016 election cycle. Exit polls painted a conflicting picture of shifts in sentiment and voter turnout among various demographics in various states. When the data becomes available, this method will be able to accuracy decouple the true nature of Republican Donald Trump's surprise victory and gains over the 2012 Republican candidate Mitt Romney.

Methodologically, we have extended the literature of MP by introducing a host of models and throwing these into a Competition-based Method of Post-stratification (CMP). While CMP in our case has not favored hierarchical linear models typically associated with MP (Park, Gelman and Bafumi, 2004; Gelman et al., 2016; Ghitza and Gelman, 2013, e.g), we note that in the realm of predicting vote choice, the advantages of multilevel models are actually less clear because the predictor space is very well defined. Especially in contexts in which the outcome variable is harder to predict, such as modeling policy preferences, CMP should yield significant advantages in MP applications.

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