Dear Gov3009ers,

Following is our paper. This is work in progress. We would appreciate any comment/suggestion you have about our statistical analysis, substance, or presentation. In particular, we included several *italicized* comments in places that need further analysis, or where we were not sure what would be the best way to go. We would appreciate your advice on these points in particular.

Looking forward to Wednesday,

Ben and Orit

But Do They Really Vote?
Correcting for Overreporting of Turnout

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Abstract

Most studies in American voting behavior employ self-reported turnout from survey data. These data inflate turnout substantially, and more important, they do so in a non-random fashion. This implies that not only are turnout rates based on self-reported turnout inaccurate, but most likely, so are estimated effects of predictors of turnout.

We propose a method that corrects for this gap. To test our method, using 1976 data, we model the relationship between validated and self-reported data. We then extrapolate and use that relationship to discount self-reported turnout in 1980. Compared to self-reported data, our test shows that our method more accurately reflects actual turnout rates, coefficients, and predicted probabilities.

We then turn to an important puzzle in current electoral behavior research: the relationship between race and turnout in the United States. Discounted data produced by our method provides different results than self-reported data. We show that the effect of race on electoral participation in 1988 and 1988 using is underestimated self-reported data.

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Introduction

Most studies of American voting behavior employ survey data, and usually such work relies on self-reported turnout (SRT). While most scholars of American political behavior agree that these data are inaccurate, there is no clear agreement about the severity of the problem and its implications for analyses of turnout. Using National Election Studies (NES) data from four recent presidential elections, this paper presents evidence that a substantial fraction of survey respondents overreport their voting turnout, and moreover overreporting is nonrandom.[1] The latter implies that not only do researchers using self-reported turnout data inflate overall turnout rates, but they are also likely to misestimate the effects of turnout predictors. We offer a theoretical account for overreporting bias, and propose an algorithm that corrects for overreporting.[2] Our proposed method uses validated data of turnout (VT) to model the relationship between validated turnout and self-reported turnout. We then extrapolate and discount overreported data in years where validation is not available or unreliable. To test the validity of this procedure, we extrapolate to a year where validated data are actually available, and test the performance of our correction against VT. Finally, we use the method to address an important issue in current voting research in the United States: the effect of race on turnout.

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[1] NES signifies the election studies begun at the University of Michigan in 1948 that have been called Center for Political Studies (CPS), Survey Research Center (SRC), or Michigan surveys.

[2] Within sample bias from overreporting is the focus of our paper. However, the discrepancy between self-reported turnout and official turnout in surveys may be a result of unit non-response bias in the sampling procedure. According to Burden (2000), over time, the NES has become more likely to miss individuals that are less engaged and harder to reach. The implicit selection mechanism is not random, and most importantly, it misses more and more non-voters over time (peaking at 28% difference between self-reported turnout and official turnout in recent years). While important, this issue is beyond the scope of our paper.

Of course, it is not clear that official turnout is accurate, either. The denominator – total voting age population – in most official measures refers to the total Voting Age Population (VAP) as reported by the Bureau of Census in their Current Population Reports, Series P-25. VAP includes all persons over the age of 18 -- including persons who are ineligible to vote in federal elections including legal and illegal aliens, persons under sentence of a felony conviction and those individuals who have been declared non compos mentis by a court of law. The VAP is therefore considerably larger than the pool of potential voters. The numerator is equal to the total number of votes cast for President in that election year (McDonald & Popkin, 2000). Many think the error from these issues is not of great consequence (e.g. Burden, 1999).

Because African Americans overreport at higher rates than whites, we argue that self-reported data may hide important differences between the two groups.

What We Know about Overreporting

About the only thing scholars agree on with regard to misreporting of turnout is that it exists and is almost entirely on one direction. The fraction of respondents voting but reporting they did not (underreporters) is negligible, and more important, these discrepancies are usually random (Presser and Traugott 1992; Silver, Anderson, Abramson, 1986). Overreporting of turnout is different. The magnitude of overreporting is much higher, and most students of voting behavior agree that overreporting is non-randomly related to voters' characteristics. However, there are several issues that make straightforward comparisons of SRT to VT difficult. The mechanism that generates overreporting of turnout, the key population of interest in measuring overreporting, the quality and accuracy of validatation procedures, and the substantive effect of overreporting are all disputed.

Silver, Anderson, and Abramson (1986) establish that non-voters tend to overreport because they want to portray themselves as engaged in a socially desirable activity. That is, *among non-voters*, those who are most likely to vote are also most likely to overreport. High education, support for democratic norms of participation, and a sense of civic duty are strong predictors of overreporting. The one empirical exception is the case of African Americans. Repeated studies have shown that African Americans are much more likely to overreport than whites, despite being less likely to turn out (Abramson and Claggett 1984, 1986, 1989, 1991).

Congruent with social-desirability theory, studies following voters over time show that overreporters tend to do so in a stable fashion (Presser and Traugott, 1992). Using panel data from the 1970s, Presser and Traugott demonstrate that non-voters who report having turned out in one election tend to do so in subsequent elections. They also establish that using SRT, political scientists overestimate partial correlations with regard to turnout. Yet – as Abramson and

Claggett's (1984, 1986, 1989, 1991) work shows – because African Americans are less likely to vote and more likely to misreport, self-reports may actually underestimate the relationship between race and voting. As a result, multivariate analyses using validated data yield more accurate coefficients but less support for standard explanations of voting behavior.

These claims are contested. First, the key population of interest is not obvious. Some argue that when measuring overreporting, scholars should control for overall turnout rate, and hence calculate overreporting as a fraction of non-voters. Silver, Anderson, and Abramson (1986) examine non-voters rather than the full sample. They argue that other measures of overreporting are sensitive to actual marginal distribution of voters and non-voters in the election, and non-voters are the actual population at risk of overreporting. However, we believe that if all individuals have a latent propensity to overreport, the general voting-age population is the relevant group by which to calculate overreporting of turnout. Because we view turnout itself as a discrete realization of an underlying tendency, we address overreporting in the full sample.

In addition, measurement of overreporting is a messy business. There are two main issues. First, the quality of the records is in question. According to Presser, Traugott, and Traugott (1990) most studies of misreporting assume that validation records and procedures are correct, and to the extent that they are incorrect, the inaccuracy is marginal and not systematic. Re-validating 1988 data, they argue that inaccuracy is more likely to occur where records are poor. Furthermore, the relationship between voters' characteristics and quality of records is not random either. For example, the authors argue that about half of measured overreporting by African Americans, a group noted for high overreporting relative to whites, may be a result of their living in areas with poor records relative to whites. However, others suggest that record quality does not systematically vary with demographic characteristics. Abramson and Claggett (1992) use several measures to argue that the tendency of African Americans to overreport is not an artifact of inferior record-keeping in areas where African Americans live.

However, even if poor record-keeping is negatively related to propensity to vote, as Presser, Traugott, and Traugott's argument implies, this would make it harder to establish Silver et al's finding of a positive relationship between propensity to vote and propensity to overreport. Those who are more likely to be incorrectly measured as overreporters are those who are *less* likely to vote. In other words, because of non-random measurement error we may misestimate the relationship between propensity to vote and propensity to misreport.

Second, some even question whether social desirability is non-random. Verba, Schlozman, and Brady (1995) propose that all individuals assess their propensity to vote and add some random positive amount to their assessment (pp. 615-617). Respondents above a certain threshold positively report. This implies that there are three types of respondents. First, respondents with a relatively low propensity to report to begin with are less likely to cross the threshold even after adding the random social desirability factor. Second, those who are below the threshold before adding the random factor but are above the threshold afterward overreport. Finally, those on the high end of the distribution report doing the act even without the exaggeration factor. We then observe a non-random curvilinear relationship in overreporting as propensity to vote increases. However, we believe their account is observationally equivalent with social desirability theory, because if one controls for the opportunities to overreport, the non-linear relationship disappears. Those who are most likely to misreport have few opportunities to do so because they vote most of the time. Regardless of which story is correct, we are still left with a positive, systematic relationship between propensity to misreport and propensity to vote that may lead to mistaken inferences about voting.

Finally, the extent of the impact of overreporting bias on our inferences about the predictors of turnout is not clear. Contrary to Silver, Anderson, and Abramson (1986), Sigelman (1982) argues that substantive conclusions about the predictors of voting, despite biased coefficients, are mostly unchanged by the use of validated as opposed to reported voting data. However, as alluded to above, there is sizable evidence that disproportionate overreporting among African Americans relative to other members of the voting population may lead to quite different conclusions about the empirical relationship between race and turnout. By demonstrating the magnitude and non-randomness of overreporting in the next section, we address these concerns and offer motivation for our project.

How Big Is the Problem?

The NES conducted vote validation studies in the 1964, 1972-80, and 1984-1990 election studies. In this paper, we focus on four most recent presidential elections with validation data: 1976, 1980, 1984, and 1988.[3] By looking at SRT, VT, and official turnouts for these years in Table 1, we can get a solid sense of the bias in SRT, and unfortunately a hint at possible error in the validation procedures in some years. The first column includes all those with data for SRT while the second column includes all respondents with data for VT. The final column presents official turnout as a baseline. Also, each row has four entries denoted 1 through 4. While the first two entries are percentage of respondents reporting to have voted, the last two are percentage of respondents whose validated data indicate they have voted. A quick look at the sample size in each cell shows that the sample with VT data is not identical to the sample with SRT data. Ideally, they should be the same. The NES in 1976 and 1980 attempted to validate each self-report, but in 1984 and 1988, self-reports were only validated if the respondent indicated she was registered or had voted in localities without registration requirements. In 1980-1988 (and for some respondents in 1976), they also validated those that completed the pre-election interview but not the post-election one (leaving such respondents without SRT data), leading to a possibility of a VT sample size greater than that of SRT, which actually occurs in 1980. In order to measure VT in the SRT sample and SRT in the VT sample, we look at those respondents with data for

[3] Respondents included in our validation sample (VT) are those with a value of 1, 3, or 5 for VAR CF9155 in the NES cumulative file, while those in the self-reported sample (SRT) are those with a value of 1 or 2 on VAR CF0702. However, if the respondents lived in areas where some or all voting records were not

both measures – the intersection of the SRT and VT samples – and this is why the sample size is identical and smaller in the off-diagonal entries (entries 2 and 3) than in the diagonal cells.

The first obvious point is that for all years, SRT in the SRT sample is greater than official figures of turnout. Second, VT in the VT sample (entry 4) is closer to official turnout than SRT in the SRT sample (entry 1) in 1976 and 1980, but still considerably over-inflates voting for these years. In 1984 and 1988 it is even higher than self-reported turnout. In other words, assuming that the validation procedures correctly determine whether or not someone votes and that official turnout figures are even roughly accurate, the validation sample in 1984 and 1988 is far from being a representative sample of U.S. voters.[4] Furthermore, while there is no apparent trend in the difference between SRT in the SRT sample and official turnout, the difference between VT in the VT sample and official turnout increases substantially from 1976 and 1980 to the 1984 and 1988 elections.

What explains this trend? A close look provides some evidence that it is not the case that people are overreporting at higher rates over time. If we compare those with measures for both SRT and VT over time (entries 2 and 3), overreporting is roughly constant across all four elections (hovering around ten percent). Yet, over time a greater fraction of respondents are lost from the SRT sample when validation studies are conducted, shown by comparing the sample size of entries 1 and 3 vis-à-vis 3 and 4 over time. Additionally, the increasing gap from 1976 and 1980 to the 1984 and 1988 elections between the fraction of those reporting voting in the validation sample and those reporting voting in the SRT sample, (entries 1 and 2) (or the similar increasing gap between the validated vote turnout in both samples, [entries 3 and 4] suggests those being lost are less likely to report voting. This all suggests that the increasing difference between validated data and official figures is caused by sampling bias. The extent of this bias is

accessible (value 2 or 5 for VAR CF9153), and researchers did not validate the respondent as voting, the respondent is removed from the sample.

so severe that self reports in the SRT sample in 1984 and 1988 represent more accurately official turnout than validated turnout in the VT sample do.

A great part of these trends is probably explained by differences in the vote validation procedures and post-election interview methodology, described in Abramson and Claggett (1986, p. 415; 1991, p. 191) and Traugott (1989). Because the changes in validation procedure in previous work were interpreted as mainly improvements and because the differences in mean overreporting are roughly constant across years, we are hesitant to suggest that the differences over time make it more difficult to examine issues of overreporting. However, the fact that the percent validated as voting in the VT sample is greater than the percent reporting voting in the SRT sample is extremely troubling. It suggests truncation in the sample. As a result, in the rest of this paper, we treat the validated data in 1976 and 1980 as actual voting behavior, but do not use disputed 1984 and 1988 data to make inferences about overreporting in the NES.

Comment*: using selection bias models, we may want to correct for the truncation in the 1984 and 1988 validation sample and use validated data in these years.*

Because we treat the question of African American turnout relative to others in the voting population, it is useful to compare their reported and validated turnout rates to those found in Table 1 for the general NES sample. Table 2 reproduces the statistics provided in Table 1 for African Americans. The fundamental difference between the two tables is the extent of the difference between VT in the SRT sample and SRT in the VT sample (again, entries 2 and 3); in Table 2 it is on average 20 percent, while in Table 1 it is at most 12 percent. Unlike in the general sample, if we compare those with measures for both SRT and VT across years, overreporting increases. However, this trend may be produced by sampling error. Similar to the case of the general population, the difference in number of respondents in the VT sample relative to the SRT sample for African Americans grows. In addition, comparing sample sizes of entries

[4] This assumption that validation procedures produce reliable, valid results may not be warranted, as noted in the literature review. Similarly, we have also noted in footnote 2 that some question the validity of official turnout figures.

1 and 3, the number of respondents with measures for both SRT and VT drops considerably relative to those with SRT alone. Finally, like the case of the general population, the increasing gap from 1976 and 1980 to the 1984 and 1988 elections between the fraction of those reporting voting in the validation sample (entry 2) and those reporting voting in the SRT sample (entry 1), or the similar increasing gap between the validated vote turnout in both samples, (entries 3 and 4), suggests that those being lost are less likely to report voting. In sum, the observations we made above for the general population hold with one crucial exception — African Americans are much more likely to overreport than whites.

This last finding leads to the next question. As explained above, even if rates of overreporting are relatively high, overreporting is only a problem for multivariate analysis if it is systematically related to our explanatory variables. Does overreporting change our inferences about the relationship of voting predictors and voting turnout? By estimating respondent's probability of voting with both VT and SRT in 1976, we can graphically get a sense of the difference between using VT and SRT in Figure 1[5]. On the x-axis are predicted probabilities of reporting having voted, estimated by logistic regression with independent variables and coefficients found in Table 3. On the y-axis are the probabilities of voting using validated data , estimated in the same manner. Each respondent represents a point on the graph. A 45-degree line is placed on the graph to show what the relationship would look like if the predicted probabilities resulting from the two measures were equal. If measurement error in self-reported data were random, the data points would spread equally above and below the diagonal across all probabilities. Those above the diagonal would be underestimated (their estimated probability of reporting voting is lower than their actual probability of voting) while those below the diagonal would be overestimated (their estimated probability of reporting to vote is higher than their actual voting).

Clearly, most respondents are below the diagonal, and in a non-random manner. Only about 7 percent of respondents are above the diagonal. We fit a quadratic relationship between the probability of voting (validated) and probability of reporting. This line shows that the overestimation is non-randomly spread. As the probability of reporting increases, the probability of overestimating one's likelihood of voting increases at a decreasing rate. The reason that some respondents with a lower likelihood of reporting to vote are actually underestimated with self-reported data is because of the non-random nature of misreporting. If those who are more likely to vote misreport more often, relationships between the predictors of voting and reporting voting will be overestimated relative to the real relationship between actual voting and such predictors. These overestimated relationships lead to the underestimation of the likelihood of voting among respondents who have characteristics that make them less likely to vote.

Finally, the non-linear relationship fits two theoretical accounts. The first possibility is put forward by Verba, Schlozman, and Brady (1995) and explained above. The other possibility is a ceiling effect. Because those who are extremely likely to vote actually vote the most, they have less of a chance to misreport than those who are slightly less likely to vote (even though they would have probably overreported had they been in a position to do so). It is those in the middle of the distribution who are most likely to have the chance to overreport. Individuals in this middle range have a higher likelihood of misreporting than those who do not vote as much, but are also less likely to vote than those with a higher probability of misreporting.

Figure 1 provides evidence that the propensity to overreport and propensity to vote are positively and non-linearly related and hints at the potential of self-reported data to lead us to mistaken inference. The evidence suggests that misreporting is indeed positively related to the probability of voting. Therefore, following the logic above, we can expect over-reporting to bias our results so that estimated relationships between voting and explanatory variables appear

[5] Based on the above observations about validated and self-reported data and the overtime trend in them, we begin our analysis with 1976 data. Even though not as recent as 1988, these data allow us to make more

stronger than they are. The one exception may be the case of race. Because African Americans are possibly less likely to vote but more likely to overreport relative to whites, overreporting may underestimate a negative relationship between being an African American and voting.

To examine these possibilities, we estimate the probability of turning out in 1980 using both self-reported turnout and validated turnout. The results of the two logistic models are presented in the first two columns of table 3 (the choice of explanatory variables is theoretically supported by Verba, Schlozman, and Brady (1995) and Rosenstone and Hansen (1993)). We note that using SRT, the relationship is overestimated. Eleven of the fifteen coefficients are overestimated, and more importantly, in the case of family income such overestimation leads to meeting a standard of statistical significance (.05 level). Additionally, in seven of eight cases where both self-reported turnout and validated turnout data show significant coefficients, the former overestimates the latter's coefficients. Consistent with what we would expect, the negative coefficient on race is positive in the SRT case. However, not much should be made of this finding given that both coefficients are insignificant.

Tables 4 and 5 gauge the effects of overreporting bias on intuitive interpretations of the right hand side variables in each model – predicted probabilities of turning out. First, in Table 4 we present predicted probabilities in the first row for a person with mean characteristics on all explanatory variables. The following rows show a person one standard deviation above the mean for each explanatory variable (all other variables held constant at their mean). Note that each SRT probability is larger than the corresponding VT probability. This difference is not accounted for by chance; the 95 percent confidence intervals do not overlap once. Table 5 provides first differences of a person moving from one standard deviation below the mean for each variable to one standard deviation above the mean, holding all other variables at their mean, to see if the generally over-estimated relationships noted in comparing the coefficients also affect first difference results in an adverse manner. Because the first differences are estimated on

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accurate inference.

coefficients with much error with relatively small samples, the overestimation in coefficients does not generally lead to statistically significant changes in interpretation of first differences. The 95 percent confidence intervals of the first differences overlap between VT and SRT for each variable.

We have presented evidence that overreporting can lead to mistaken inference, mostly through the overestimation of coefficients that in some cases make variables appear to be significantly related to voting when they are in fact not. Having established the magnitude of the problem, we now turn to propose a possible solution.

Solution

Our algorithm improves upon voting estimates generated with self-reported data by correcting for two types of errors caused by overreporting. First, it produces more accurate turnout rates both in the general voting population and within segments of it that are of interest to scholars of voting behavior. Second, it provides more accurate estimates of the effects of turnout predictors.

The logic is straightforward: model the relationship between voting and reporting voting at time t (where validated data are available), and use that model to discount self-reported turnout data at time t+1, where validated data are not available. In this section we provide a detailed description of our correction algorithm.

Step 1: Model the relationship between voting and reporting of vote at time t

1a. Estimate SRT at the individual level at time t (equation 1.1). This is a standard turnout model, theoretically supported by Verba, Schlozman, and Brady (1995) and Rosenstone and Hansen (1993):

$$\Pr(SRT = 1) = f_1(X, \beta_1, \varepsilon_1) \tag{1.1}$$

where X is a vector of voter characteristics

β_1 is a vector of coefficients, and

ε_1 is a random component

Further, calculate estimated predicted probabilities to report voting for each individual:

$$\hat{\Pr}(SRT = 1) = f_1\left(X, \hat{\beta}_1\right) \tag{1.2}$$

1b. Similarly, estimate a model of VT at the individual level at time t (equation 1.3).

$$\Pr(VT = 1) = f_1(X, \beta_2, \varepsilon_2) \tag{1.3}$$

Further, calculate the estimated predicted probability to report voting for each individual:

$$\hat{\Pr}(VT = 1) = f_1\left(X, \hat{\beta}_2\right) \tag{1.4}$$

1c. The Discounting Function

Model the relationship between voting and reporting of vote. Based on the quadratic relationship observed by Verba, Schlozman, and Brady and presented in figure 1, we include a quadratic term in our right-hand side:

$$\hat{\Pr}(VT = 1) = d(Z, \delta, \upsilon) \tag{1.5}$$

where $Z = (\hat{\Pr}(SRT = 1), \hat{\Pr}(SRT = 1)^2)$ at time t

δ is a vector of coefficients, and

υ is a random component

One might wonder why we model the predicted probability of voting as a function of the predicted probability of reporting vote, rather than *observed* VT as a function of *observed* SRT and explanatory variables:[6]

$$\Pr(VT = 1) = g(X, SRT, \gamma, \upsilon_2) \tag{1.5a}$$

where X is a vector of voter characteristics

γ is a vector of coefficients, and

[6] Katz (1999) offers a somewhat similar method, where he models overreporting as a function of voter characteristics, among other things.

υ_2 is a random component

This point is key. Recall that the goal is to use the discounting function to correct self-reported data at t+1. While the two alternatives offer discount of SRT, they implicitly rely on different assumptions. Our correction algorithm assumes that social desirability – the process that maps VT to SRT (i.e. the δ coefficients) – is constant between t and t+1. Our method is, in turn, robust changes overtime in the effects of predictors of turnout (we need not assume that β's are constant over time). The alternative, on the other hand, implicitly assumes that effects of turnout predictors are constant between t and t+1. This is a tradeoff between restrictive assumptions and additional noise in the estimation process. Our method is less restrictive in the assumptions it makes, yet not without cost: it involves an additional step of estimation, and thus introduces additional noise.

Comment: *The two assumptions are, in fact, empirically testable. While the current version of the project includes a test for our assumption only, we hope that the absence of the alternative assumption does not tax the reader too much.*

Step 2: Use the discounting function to correct data at t+1

Having modeled the relationship between VT and SRT, use this function to discount self-reported data in year t+1, where validated data do not exist.

2a - 2b. Estimate SRT at the individual level at time t+1 and compute predicted probability of reporting vote for each individual (equations 2.1, 2.2).

$$\Pr(SRT = 1) = f_1(X, \beta_3, \varepsilon_3) \tag{2.1}$$

$$\hat{\Pr}(SRT = 1) = f_1(X, \hat{\beta}_3) \tag{2.2}$$

This stage produces SRT probability for each individual at time t+1.

2c. Apply the discounting function to t+1 data:

$$\hat{\Pr}(DSRT = 1) = d(Z, \hat{\delta}) \tag{2.3}$$

where DSRT is the individual's discounted probability of turning out, and

$$Z = (\hat{\Pr}(SRT = 1), \hat{\Pr}(SRT = 1)^2) \text{ at time t+1}$$

2d. Map the discounted probabilities to dichotomous pseudo data. Up to this point, our method produced discounted predicted probabilities of turning out. While valuable, this is not satisfactory if one wishes to better understand turnout employing conventional analysis. This step therefore, converts the probabilities to a dichotomous variable similar in form to the original observed SRT.

Comment: *We are not sure that we would like to stick to this step. Would it make sense to keep the Phats, rather than converting them to a dichotomous quantity?*

Step 3: Estimate turnout on the discounted dichotomous data at t+1

Reestimate turnout on the discounted dichotomous data at time t+1 (equation 3.1)

$$\Pr(pseudo\_SRT = 1) = f_4(X, \beta_4, \varepsilon_4) \tag{3.1}$$

This step allows us to compare the effects on self-reported turnout (β_1) to the effects on discounted turnout (β_4) and (hopefully) better understand what predicts turnout.

Multiple-stage estimation

Although the logic of our algorithm is straight forward, correcting data using auxiliary information in a multiple-step estimation process can get a bit messy. Each step in the process yields results, which then turn into input for the next step. Our estimation algorithm includes several sources of estimation uncertainty, as well as fundamental uncertainty.[7]

The first source is the uncertainty around the coefficients on SRT and VT at time t (β_1 and β_2, respectively), producing the predicted probabilities for the two variables. Similarly, the coefficients on SRT at time t+1 (β_3), which are used to produce predicted probabilities to be discounted, have uncertainty around them. Third, the coefficients in the discounting function (δ), which map the relationship between the two sets of predicted probabilities from the first source,

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[7] For a comprehensive discussion of fundamental and estimation uncertainty, see King, Tomz, and Wittenberg, 2000. self-reported turnout and validated turnout

face similar uncertainty issues. Finally, the mapping of the discounted probabilities to dichotomous pseudo data involves one additional layer of uncertainty.

Using Monte Carlo simulations and randomly drawing from the respective distributions, we account for these various sources of uncertainty. For the second and third sources of uncertainty, we randomly draw from the respective multivariate normal distributions. As for the last source, to account for uncertainty we generate a vector of zeros and ones for each individual. The probability of an individual scoring a one is equal in expectation to the discounted probability.

Comment: *We first ran a crude version of the algorithm, and only then added uncertainty. As this work is very much in progress, the results presented here do not account for the first source of uncertainty, but only for the second through fourth levels. The current version, then, takes the predicted probabilities of SRT and VT (equation 1.5) as given.*

Testing Our Method

In order for our measure of voting turnout to be useful, it should be closer than SRT to the results generated by VT – conditioning on the same model. Recall, in 1980 overestimated the relationship of several predictors of voting when compared to VT (table 3), and in turn the fitted values for SRT were consistently higher than those of VT (table 4).

How well does our algorithm perform? To test our method, we estimate our discounting function in 1976 and use it to discount self-reported data 1980. We then compare the results to both self-reported turnout and validated turnout in 1980. This is ideal out-of-sample test as the validated data in 1980 provides a standard by which we evaluate our results.[8]

The third column of table 3 presents estimated coefficients on our discounted self-reported turnout (DSRT). We compare these coefficients to the ones produced by VT as well as SRT. Eyeballing the coefficients, note that our results are more accurate than SRT alone (i.e. closer to VT) on twelve out of the fifteen variables. In particular, note the income coefficient.

[8] Our right hand side variables used in steps 1a, 1b, 2a, and 3 are the same, yet they need not be. The number of draws/simulations accounting for each source of uncertainty is 800.

While SRT overestimates the relationship to the extent that a non-significant relationship seems significant, the estimate produced by our method is similar to the VT estimate.

As for fitted values presented in Table 4, our method provides values that are statistically speaking no different from those using VT. For each variable, the 95 percent confidence interval of VT and discounted SRT overlap (as noted above, SRT confidence intervals do not overlap with VT for any of the variables). In sum, our measure provides much more accurate predicted probabilities of voting than those produced by SRT alone.

In addition to these performance tests, we report two robustness tests of our algorithm. First, we estimated the relationship between self-reported turnout and validated turnout in all available years. Table 6 presents the discounting function in 1976, 1980 1984, and 1988. As shown in the table, the relationship is almost identical in 1976 and 1980. It is also similar between 1984 and 1988. The coefficients, however, change between the first two data points and the last two. Note that this change corresponds with the change in the sample (discussed in table 1). Therefore, we do not interpret the change in coefficients as an indication that social desirability has changed over time. Rather, we conclude that the 1984 and 1988 samples do not allow us to evaluate the constancy of social desirability.

Second, we perform an in-sample test. We discount 1980 self reports by the discounting function produced by 1980 data itself. We compare the results to the results produced by the same data discounted by 1976 discounting function (column 4 in tables 3, 4, and 5). For all quantities of interest, the two sets of results are statistically the same, element by element.

Comments: *As for the first test, maybe we should correct for selection bias in 1984 and 1988 and then test it? Also, we should probably compare goodness of fit of the discounting function over time (does SRT predict VT with the same accuracy over time?). As for the second test, here too we should still compare goodness of fit between the first and third column, as well as between the third and fourth.*

Race and Overreporting

In a series of articles, Abramson and Claggett (1984, 1986, 1989, 1991) examine the level of electoral participation of African Americans and whites and explore whether education and region explain differences in turnout. Using self-reported data, the authors usually find no significant difference between African Americans and whites controlling for education and living in the South. Yet using validated data, they find a very different story: compared to whites, African Americans are less likely to participate in elections. In other words, African Americans overreport at vastly higher rates than whites, yet are less likely to turn out compared to whites. Their self-reports of high turnout and their tendency to turn out at low rates work in opposite directions. Consequently, researchers using SRT may underestimate the effect of race on turnout.

In this section, we use our method to address this issue. First, we apply our method with a few modifications to suit the particular problem at hand to the 1980 voting data. Using a model and variables similar to Abramson and Claggett, we show that results using our generated discounted data provide similar results to those produced using VT data.[9] The modifications of our algorithm are described in detail in the appendix, but to put it simply, we pool the validated data from 1976 and 1980, and allow the discounting function to vary with race. Given our test of the discounting function coefficients over time (see table 6) and the distribution of the data presented in table 1, pooling the data from these two points seems a safe choice. We repeat this procedure in 1984 and 1988 where validated data are skewed, and propose that the use of SRT most likely leads to mistaken inferences about racial differences in 1980s presidential elections. The use of the skewed VT, on the other hand, incorrectly 'repairs' self-reported data.

Following Abramson and Claggett, we examine whether racial differences in turnout persist controlling for education and region. We present two logit models. The first model has

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[9] This is not a complete replication of Abramson and Claggett's work. We code our variables in a slightly different manner. AC code the race variable as a dichotomous –1, 1 variable. We employ the standard dummy approach (0, 1). Despite these differences in procedure, our results are very similar to those of

only race on the right-hand side. The second model controls for education and living in the South. Table 7 presents predicted probabilities comparing African Americans turnout rates to whites in the sample in 1980. The second and third rows in each model provide mean predicted probabilities for the two groups, with the other explanatory variables held at their mean, while the first row presents the mean difference between the two groups. The last row provides a baseline – the mean predicted probability.

In 1980, SRT and VT produce different results. In the thin model, both SRT and VT show differences in turnout across race (African Americans are less likely to turn out), yet using VT, the difference substantially is greater (.105 compared to .058 using SRT). In model 2, the results are somewhat weaker: using both SRT and VT, there is no significant difference between African Americans and others (the confidence intervals of the first differences contain zero). In both models, our method produces probabilities more accurate than SRT and close to validated data. In the first model we find a significant difference of .121, and in the controlled model we find no significant effect of race.

Moving to 1984 and 1988 where validated data are skewed, we compare the results produced by SRT to results produced by our method as well as validated turnout (Tables 8 and 9, respectively). First, note the benchmark comparison in 1984: predicted probability of turning out in the full sample is higher using VT than using VT (with predicted turnout of eighty one percent vs. seventy five percent in model 1, and eighty two vs. seventy six percent in model 2). The predicted overall turnout using our method is less inflated than both VT and SRT (sixty seven percent in both models). The same holds when breaking down turnout by race. In both models, predicted turnout using validated data is higher than turnout using self-reported turnout. Our measure produces the most reasonable results. This, in combination with our table 1, makes us again suspicious about the use of validated data in 1984.

Abramson and Claggett using SRT and VT in the elections we address in this paper (1976, 1980, 1984, 1988).

Using SRT in 1984, the first model shows a nine percent difference between African Americans and others. Controlling for education and region, the difference in predicted probabilities of turning out disappears (0.03 non-significant difference). VT shows a substantial significant difference: African Americans are less likely to turn out by nineteen percentage points in the thin model, and by thirteen percentage points, controlling for education and region. Our method shows a toned down picture: African Americans turn out less then others (with a gap of fifteen percent in the thin model and nine percent in the second model). In model 2 no statistical difference using SRT becomes a significant negative effect using our method, and in model 1, a small difference turns out to be greater.

Our findings in 1988 (table 9) follow a similar trend. First notice that for almost all cases predicted turnout using validated data is higher than self-reported data (with eighty vs. seventy percent in full sample of model 1 and eighty vs. seventy two percent in model 2). Our predicted quantities are smaller then both (sixty three and sixty four percent, respectively).

SRT in the thin model shows a difference across race in propensity to vote (fifty nine percent for African Americans vs. seventy one percent for whites, on average), and the difference disappears once controlling for education and region. Our method, on the other hand, shows a negative effect: a sixteen percent difference in the thin model, and about eleven percent in model 2. Again, investigating the effect of race on turnout using self-reported data alone yields questionable findings.

To sum up, our findings in this section lead us to two main conclusions. First, self-reported data can produce inaccurate results when investigating substantive questions with regard to turnout. These findings highlight the importance of validation studies. Second, validated data in 1984 and 1988 (data that are systematically skewed) are not satisfactory either. Our method with the combination of better data (1976 and 1980) allows to extrapolate to years where trustworthy data do not exist, and explore substantive political puzzles.

Conclusion

Survey data is a crucial resource for scholars of political behavior. While sophisticated survey methodology can shed light on important puzzles in political behavior, in some circumstances survey response should not be taken at face value.

Electoral participation is one such case. The variable scholars are often interested in – turning out – is not identical to the variable observed – report of turning out. The latter is inflated compared to the former. Depending on the empirical puzzle, this gap may affect the analysis, and lead to incorrect findings.

Comparing validated to self-reported data over time, this project adds new evidence to an extensive body of literature. We show that using self-reported data, when asking "Who Votes?" political scientists usually overestimate the effects of turnout predictors, with the exception of race – its effect is underestimated. This seems curious. Some partial correlations are overestimated, yet others are underestimated. The explanation, we propose, lies in the data-generating process.

Given the discrepancies between the observed and unobserved data, it is useful to think of two data-generating processes. The first process predicts turnout, while the second predicts report of turnout. In general, individuals who are more likely to vote, are more likely to report having voted, even if they did not. That is, the same individual characteristics that predict high probability of turning out, predict high probability of positive report of turnout. The two data-generating mechanisms are positively correlated. Using the observed variable, we then overestimate the effects of individual characteristics.

The case of African Americans works in an opposite way. African Americans are less likely to vote compared to others, yet more likely to overreport. That is, the individual characteristic (race) that predicts low likelihood of turning out, also predicts *high* likelihood of positive report of turning out. The two effects work in opposite directions and mask each other. Consequently, using self-reported data alone, the effect of race is underestimated.

The source of the bias, then, is the relationship between the mechanism generating the observed data and the mechanism generating the unobserved data. Overreporting is not random. Ignoring this issue leads political scientists to biased findings when investigating substantive puzzles. Unpacking the nonrandomness, as we show, is crucial for arriving at accurate answers in studies of voting behavior.

Our method models these insights and offers a solution to the problem. Testing our algorithm against validated data when available both generally and in a specific empirical application, we show that we arrive at more accurate results than self-reported data alone.

Finally, our findings have general application beyond the issue of overreporting. First, at the very least, our exploration should alert the reader to the potential perils of electoral behavior research using survey data. The possibility of mistaken inference given current data is not negligible, and care should be taken to make sure one's findings are not the product of typical bias and error in social science data.

Our results also demonstrate the need for further validation studies. Our approach can be applied as a means to make future validation studies more economical. By validating a sub-sample of respondents and estimating the discount function these individuals, researchers can discount self-reports in the full sample. Our method need not be restricted to extrapolation over time, we can also cross-sectionally interpolate.

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Table 1. Self-Reported Turnout, Validated Turnout and Official Turnout by Year

Year		Self-Reported Sample		Validated Sample	Official Turnout*
1976	**(1)**	**72.9 %**	**(2)**	**74.6**	**53.6**
%SRT=1		(70.9, 74.9)		(72.5, 76.6)	
		n=1909		n=1788	
%VT=1	**(3)**	**64.5**	**(4)**	**64.5**	
		(62.3, 66.7)		(62.3, 66.7)	
		n=1788		n=1860	
1980		**71.4**		**71.5**	**52.6**
%SRT=1		(69.0, 73.7)		(69.0, 74.0)	
		n=1407		n=1278	
%VT=1		**61.3**		**58.6**	
		(58.6, 63.9)		(56.1, 61.1)	
		n=1278		n=1471	
1984		**73.6**		**89.8**	**53.1**
%SRT=1		(71.7, 75.5)		(88.3, 91.3)	
		n=1989		n=1575	
%VT=1		**79.4**		**74.9**	
		(77.4, 81.4)		(72.9, 76.9)	
		n=1575		n=1815	
1988		**69.7**		**89.0**	**50.6**
%SRT=1		(67.5, 71.8)		(87.3, 90.7)	
		n=1773		n=1305	
%VT=1		**79.2**		**74.7**	
		(77.0, 81.4)		(72.5, 76.9)	
		n=1305		n=1519	

Cell entries include: rate, 95% confidence interval, and number of respondents, respectively. The SRT sample includes respondents who have reported data, while the VT sample includes all those with validated data. The fraction with VT=1 in the SRT sample and the fraction with SRT=1 in the VT sample are those respondents with both SRT and VT data. This table does not use the post-stratification weights provided by the NES.
*Official turnout figures are from the Federal Election Commission, http://www.fec.gov/pages/tonote.htm (link active as of 8/20/00).

Table 2. Self-Reported Turnout, Validated Turnout and Official Turnout for African Americans by Year

Year		Self-Reported Sample		Validated Sample
1976	**(1)**	**66.1%**	**(2)**	**67.7**
%SRT=1		(58.9, 73.2)		(60.4, 75.1)
		n=171		n=158
%VT=1	**(3)**	**50.6**	**(4)**	**52.1**
		(42.8, 58.5)		(44.5, 59.7)
		n=158		n=169
1980		**66.7**		**66.2**
%SRT=1		(59.4, 73.9)		(58.3, 74.1)
		n=165		n=142
%VT=1		**52.8**		**49.4**
		(44.5, 61.1)		(41.6, 57.2)
		n=142		n=162
1984		**65.6**		**84.0**
%SRT=1		(59.2, 72.0)		(78.4, 89.7)
		n=215		n=163
%VT=1		**63.2**		**58.7**
		(55.7, 70.7)		(51.7, 65.6)
		n=163		n=196
1988		**59.7**		**80.7**
%SRT=1		(53.1, 66.3)		(74.2, 87.2)
		n=216		n=145
%VT=1		**58.6**		**55.1**
		(50.5, 66.7)		(47.9, 62.3)
		n=145		n=187

Cell entries include: rate, 95% confidence interval, and number of respondents, respectively. The SRT sample includes respondents who have reported data, while the VT sample includes all those with validated data. The fraction with VT=1 in the SRT sample and the fraction with SRT=1 in the VT sample are those respondents with both SRT and VT data. This table does not use the post-stratification weights provided by the NES.

Table 3. 1980 Validated Turnout, Self-Reported Turnout, and Discounted Self-Reported Turnout Logistic Regression Coefficients

Explanatory Variable	Validated Turnout Coefficients	Self-Reported Turnout Coefficients	Discounted Self-Reported Turnout (using 1976 data)	Discounted Self-Reported Turnout (using 1980 data)
Education	**0.532***	**0.677***	**0.519***	**0.517***
	(0.070)	(0.077)	(0.067)	(0.067)
Family Income	**0.124**	**0.173***	**0.138**	**0.138**
	(0.0761)	(0.082)	(0.073)	(0.073)
Male	**0.276**	**0.274**	**0.216**	**0.206**
	(0.142)	(0.151)	(0.135)	(0.135)
South	**-0.221**	**-0.030**	**-0.039**	**-0.036**
	(0.154)	(0.151)	(0.147)	(0.147)
African American	**-0.107**	**0.1525**	**0.119**	**0.106**
	(0.230)	(0.2264)	(0.214)	(0.213)
Age1724	**-1.008***	**-1.260***	**-1.001***	**-0.990***
	(0.280)	(0.286)	(0.259)	(0.258)
Age2534	**-0.666***	**-0.818***	**-0.629***	**-0.631***
	(0.249)	(0.262)	(0.228)	(0.228)
Age3544	**-0.094**	**-0.157**	**-0.123**	**-0.127**
	(0.286)	(0.286)	(0.244)	(0.243)
Age5564	**0.070**	**0.298**	**0.229**	**0.233**
	(0.271)	(0.311)	(0.265)	(0.265)
Age65ov	**0.408**	**0.487**	**0.382**	**0.370**
	(0.282)	(0.305)	(0.263)	(0.262)
Homeowner	**0.553***	**0.474***	**0.379***	**0.349***
	(0.163)	(0.170)	(0.156)	(0.156)
Church attendance	**0.204***	**0.211***	**0.164***	**0.167***
	(0.047)	(0.051)	(0.045)	(0.045)
PID (strength)	**0.276***	**0.375***	**0.289***	**0.292***
	(0.072)	(0.076)	(0.069)	(0.069)
Contact	**0.345***	**0.816***	**0.625***	**0.605***
	(0.171)	(0.202)	(0.167)	(0.167)
Constant	**-3.089***	**-3.432***	**-3.019***	**-2.999***
	(0.416)	(0.449)	(0.399)	(0.399)
N	1121	1235	1235	1235

Standard error in parentheses, p<.05=*

Table 4. 1980 Validated, Self-reported, and Discounted Self-reported Data Fitted Values

Explanatory Variable	Pr (Validated Turnout) =1	Pr (Self-Reported Turnout) =1	Pr (Discounted Self-Reported Turnout) = 1, using 1976 data	Pr (Discounted Self-Reported Turnout) = 1, using 1980 data
Mean	**.647**	**.776**	**.647**	**.647**
	(.615, .677)	(.745, .802)	(.616, .676)	(.616, .675)
Education	**.777**	**.886**	**.774**	**.775**
	(.738, .817)	(.855, .911)	(.733, .810)	(.737, .810)
Family Income	**.678**	**.808**	**.681**	**.682**
	(.628, .722)	(.770, .848)	(.639, .724)	(.636, .725)
Male	**.678**	**.797**	**.671**	**.669**
	(.634, .715)	(.760, .833)	(.630, .710)	(.624, .709)
South	**.624**	**.774**	**.643**	**.643**
	(.581, .668)	(.736, .810)	(.598, .686)	(.600, .684)
African American	**.639**	**.784**	**.655**	**.655**
	(.595, .682)	(.748, .819)	(.613, .695)	(.613, .693)
Age1724	**.567**	**.694**	**.565**	**.565**
	(.512, .615)	(.642, .740)	(.513, .614)	(.510, .617)
Age2534	**.580**	**.709**	**.583**	**.582**
	(.521, .635)	(.652, .757)	(.527, .636)	(.526, .634)
Age3544	**.639**	**.766**	**.636**	**.635**
	(.582, .691)	(.714, .809)	(.581, .684)	(.580, .685)
Age5564	**.652**	**.793**	**.664**	**.663**
	(.606, .702)	(.745, .833)	(.610, .711)	(.607, .711)
Age65ov	**.681**	**.805**	**.678**	**.677**
	(.632, .728)	(.756, .844)	(.625, .726)	(.620, .724)
Homeowner	**.702**	**.812**	**.687**	**.683**
	(.658, .739)	(.774, .846)	(.648, .729)	(.641, .727)
Church attendance	**.714**	**.826**	**.701**	**.703**
	(.669, .752)	(.788, .857)	(.658, .738)	(.660, .741)
PID (strength)	**.706**	**.833**	**.709**	**.710**
	(.662, .749)	(.797, .865)	(.668, .745)	(.664, .748)
Contact	**.680**	**.830**	**.705**	**.703**
	(.635, .722)	(.793, .862)	(.662, .746)	(.660, .743)
N	1121	1235	1235	1235

Mean equals predicted probability for mean respondent. All other entries present mean predicted probabilities for respondents scoring one standard deviation above the mean for the row variable. In parentheses is the 95% confidence interval.

Table 5. 1980 Validated, Self-Reported Turnout, and Discounted Self-Reported Turnout First Differences (Mean – SD to Mean + SD)

Explanatory Variable	Validated Turnout	Self-Reported Turnout	Discounted Self-Reported Turnout 76-80	Discounted Self-Reported Turnout 80-80
Education	**.286**	**.279**	**.279**	**.281**
	(.215, .360)	(.223, .337)	(.213, .400)	(.215, .344)
Family Income	**.063**	**.070**	**.070**	**.072**
	(-.015, .143)	(.014, .133)	(.001, .146)	(.004, .146)
Male	**.063**	**.045**	**.049**	**.046**
	(.001, .123)	(-.009, .096)	(-.014, .106)	(-.014, .105)
South	**-.045**	**-.004**	**-.007**	**-.008**
	(-.103, .020)	(-.052, .044)	(-.068, .053)	(-.067, .050)
African American	**-.016**	**.017**	**.017**	**.016**
	(-.075, .046)	(-.031, .067)	(-.038, .072)	(-.041, .071)
Age1724	**-.152**	**-.147**	**-.155**	**-.156**
	(-.231, -.072)	(-.217, .081)	(-.233, -.072)	(-.228, -.081)
Age2534	**-.128**	**-.120**	**-.122**	**-.125**
	(-.219, -.035)	(-.200, -.042)	(-.205, -.032)	(-.212, -.039)
Age3544	**-.014**	**-.019**	**-.022**	**-.024**
	(-.108, .079)	(-.088, .057)	(-.105, .060)	(-.105, .056)
Age5564	**.011**	**.035**	**.035**	**.033**
	(-.072, .090)	(-.037, .109)	(-.043, .110)	(-.055, .109)
Age65ov	**.070**	**.063**	**.065**	**.062**
	(-.020, .156)	(-.016, .137)	(-.022, .147)	(-.027, .147)
Homeowner	**.114**	**.078**	**.082**	**.074**
	(.048, .176)	(.023, .133)	(.021, .144)	(.007, .136)
Church attendance	**.141**	**.110**	**.113**	**.116**
	(.079, .205)	(.056, .161)	(.053, .171)	(.056, .177)
PID (strength)	**.124**	**.129**	**.131**	**.131**
	(.060, .186)	(.076, .178)	(.070, .190)	(.069, .193)
Contact	**.068**	**.120**	**.122**	**.118**
	(.000, .136)	(.060, .178)	(.059, .183)	(.055, .176)
N	1121	1235	1235	1235

All entries present predicted mean difference in the probability for a respondent moving from one standard deviation below the mean to one standard deviation above the mean for the row variable.
In parentheses is the 95% confidence interval.

Table 6: Discounting Function Coefficients – 1976 through 1988

Year	Constant	Self-Reported Turnout	Self-Reported Turnout – squared
1976	**0.101** (0.014)	**0.365** (0.047)	**0.491** (0.036)
1980	**0.102** (0.009)	**0.350** (0.031)	**0.471** (0.025)
1984	**0.310** (0.013)	**0.704** (0.044)	**-0.085** (0.034)
1988	**0.382** (0.010)	**0.551** (0.037)	**-0.029** (0.030)

Standard errors in parentheses

Table 7. Probabilities of Turning Out by Race: 1980 Presidential Election

	Self-Reported Turnout	Discounted Self-Reported Turnout	Validated Turnout
		Model 1	
Difference b/w African Americans and Others	**-.058** (-.145, -.025)	**-.121** (-.209, -.035)	**-.105** (-.193, -.014)
African Americans	**.671** (.592, .750)	**.545** (.459, .627)	**.529** (.440, .616)
Whites	**.729** (.701, .756)	**.666** (.638, .693)	**.634** (.604, .664)
Full Sample	**.723** (.695, .749)	**.653** (.627, .680)	**.623** (.595, .652)
		Model 2	
Difference b/w African Americans and Others	**-.012** (-.210, .129)	**-.064** (-.156, .020)	**-.053** (-.149, .038)
African Americans	**.724** (.544, .846)	**.603** (.475, .624)	**.583** (.493, .670)
Whites	**.736** (.708, .765)	**.667** (.637, .695)	**.636** (.605, .667)
Full Sample	**.735** (.709, .758)	**.660** (.631, .686)	**.630** (.604, .659)

Model 1: Race
Model 2: Race, Education, and Region (South vs. other)
Entries in the table are predicted probabilities for individual with mean characteristics.
95% confidence interval in parentheses.

Table 8. Probabilities of Turning Out by Race: 1984 Presidential Election

	Self-Reported Turnout	Discounted Self-Reported Turnout	Validated Turnout
		Model 1	
Difference b/w African Americans and Others	**-.093** (-.164, -.031)	**-.148** (-.224, -.070)	**-.185** (-.267, -.107)
African Americans	**.662** (.592, .723)	**.533** (.460, .603)	**.644** (.563, .718)
Whites	**.756** (.734, .777)	**.681** (.656, .707)	**.830** (.807, .850)
Full Sample	**.747** (.726, .767)	**.665** (.642, 689)	**.814** (.792, .834)
		Model 2	
Difference b/w African Americans and Others	**-.030** (-.104, .034)	**-.088** (-.165, -.007)	**-.131** (-.210, -.058)
African Americans	**.733** (.664, .793)	**.594** (.518, .668)	**.697** (.621, 769)
Whites	**.763** (.740, .785)	**.682** (.659, .705)	**.829** (.805, .849)
Full Sample	**.760** (.739, .780)	**.673** (.650, .695)	**.817** (.795, .837)

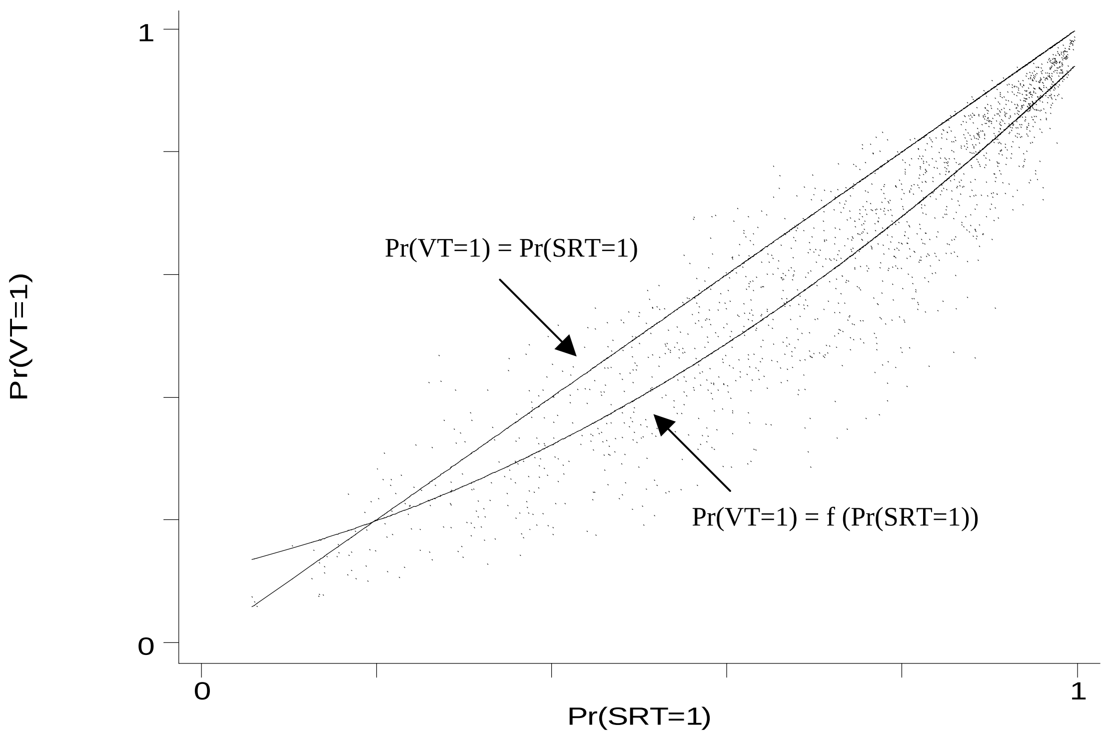
Model 1: Race
Model 2: Race, Education, and Region (South vs. other)
Entries in the table are predicted probabilities for individual with mean characteristics.
95% confidence interval in parentheses.

Table 9. Probabilities of Turning Out by Race: 1988 Presidential Election

	Self-Reported Turnout	Discounted Self-Reported Turnout	Validated Turnout
		Model 1	
Difference b/w African Americans and Others	**-.120** (-.195, -.042)	**-.160** (-.237, -.083)	**-.240** (-.332, -.151)
African Americans	**.595** (.524, .667)	**.486** (.415, .559)	**.580** (.492, .665)
Whites	**.714** (.689, .737)	**.646** (.620, .672)	**.820** (.797, .842)
Full Sample	**.700** (.677, .722)	**.627** (.602, .650)	**.799** (.777, .820)
		Model 2	
Difference b/w African Americans and Others	**-.065** (-.148, .010)	**-.112** (-.190, -.034)	**-.229** (-.319, -.148)
African Americans	**.663** (.581, .730)	**.538** (.461, .608)	**.592** (.504, .670)
Whites	**.728** (.702, .751)	**.650** (.622, .676)	**.822** (.796, .845)
Full Sample	**.721** (.695, .743)	**.636** (.610, .662)	**.801** (.777, .826)

Model 1: Race
Model 2: Race, Education, and Region (South vs. other)
Entries in the table are predicted probabilities for individual with mean characteristics.
95% confidence interval in parentheses.

Figure 1. Probability of Voting (Validated) by Probability of Reporting in 1976



Appendix

Given our substantive interest and the idiosyncrasies of the data discussed, we propose several refinements of the general method – refinements that take into account the specific constraints of the data available to us. While the general form provides a worthy solution to biases in reporting of turnout, the context-specific refinements we employ help us to better investigate our substantive question. We list here in more detail the modifications of the algorithm that we use to investigate the effect of race on turnout.

The first modification has to do with the number of time slices available to us. When predicting 1984 and 1988, we pool the trustworthy data available (that is 1976, 1980), rather than one time slice only.

Second, given our hypotheses about African Americans, we allow the discounting function to vary with race. We include both a race dummy variable and an interaction term. The relationship between SRT and VT at time t, and therefore the discount rate for SRT at t+1 (steps 1c and 2c, respectively) are different for African Americans and others. Table A presents the model specification, as well as 1980 coefficient estimates.

Comment: *Given that we 'know' that race is relevant, and we explicitly include it in our discounting model for our application, should we include it in our generic algorithm as well? The reason we do not so far is because we wanted to have a general and simple algorithm, but it makes the two parts seem somewhat inconsistent with each other. We would appreciate your advice on this point as well. Thanks!*

Table A. The Discounting Function and Coefficient Estimates for 1980

Variable	Coefficient
African American	**-0.027**
	(0.028)
Pr(SRT=1)	**0.377**
	(0.055)
Pr(SRT=1)^2	**0.461**
	(0.041)
African American * Pr(SRT=1)	**-0.178**
	(0.093)
African American * Pr(SRT=1)^2	**0.169**
	(0.074)
Constant	**0.124**
	(0.018)

Standard errors in parentheses