# The Partisan Effects of Voter Turnout

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March 29, 2004

## 1 The Problem

According to the *Washington Post*, Republicans are urged to pray for poor weather on national election days, so that voter turnout is decreased, thus strengthening the party's prospects for victory. While this is an extreme example, it is emblematic of a belief that has taken deep root in the conventional wisdom on American electoral outcomes: that the Republican Party benefits from reduced turnout.

The only problem is that rudimentary analysis of the data shows quite the opposite. Republicans actually do consistently better with higher turnout rather than lower turnout. So is the conventional wisdom wrong or are the statistics flawed in some way? Unfortunately the theory is quite ambiguous on the subject, and while the theoretical backing for the theory that Republicans do better with higher turnout seems to have a little more traction, its advantages are not nearly enough to make it clear as to what the true answer is.

Before proceeding, we should probably briefly discuss why, indeed, this is an interesting subject, beyond that it can provide a forum for the implementation of some fun statistical techniques. First of all, the two parties spend a significant amount of time playing with the rules about voter eligibility, with the Republicans usually trying to hamper Democratic efforts to make it easier to qualify to vote. If they are behaving irrationally, that itself would be an interesting starting point for another study. Additionally, the use of data to try to bolster either one of the competing theories will shed more

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light on how to best model voting behavior. Finally, a better model of the interrelationship between turnout and partisan results could perhaps allow more detailed "prediction" of election results.

So why is this a hard problem? It essentially boils down to the endogeneity of turnout. As we have seen before, canvassing does increase turnout. Of course, the canvassing efforts of parties are dependent on their beliefs about the partisanship of a particular precinct, so the standard assumptions of OLS will fail, as the errors will be correlated with some of the independent variables. Additionally, there are effects that occur on the individual voter level–like people being less likely to vote in landslide elections–that further complicate the analysis.

## 2 Existing Analyses

Beginning with DeNardo, (1980) many scholars have sought to determine the empirical relationship between turnout and the partisan vote for president. DeNardo's (1980) work found itself quickly debunked as it was based upon national returns, which eliminated much of the variation that could be observed and added the confounding variable of voting rights in the South.

Though there were attempts (Tucker and Verdlitz, 1986; DeNardo, 1986) to unravel the relationship before his, Radcliff (1994a) broke new ground with estimates of turnout's effect on state level presidential returns from 1948 to 1980. Specifically, he used two major methodologies. In one, he simply pooled all of his data and regressed results on turnout, as well as economics statistics, incumbency, and dummy variables for year and state. In the other, he follows DeNardo's (1980) House methodology and stratifies his sample by how Democratic states are. In both cases he finds that turnout significantly helps Democrats. His results were not immune to criticism as Erikson (1994a) claimed that all he was seeing was the impact of the voting rights revolution in the South. Controlling for that, the relationship disappeared.

Seeking to resolve the disagreement of their senatorial and gubernatorial data (1996) with Radcliff's (1994a) data, Nagel and McNulty (2000) regressed results on turnout, incumbency, and state dummies. Though their data set is more modern, going through 1996, their analysis is critically flawed in that they do not account for economic variation or other temporal variation.

Of course, none of these above analyses even begin to address the issue of endogeneity. To that end we should note that there is some literature focusing on some natural experiments. While this literature does not explicitly measure the impact of turnout on results, it is worth briefly reviewing what has been done.

Franklin and Grier (1997) examined how the adoption of motor voter laws impacts turnout and electoral results. Controlling for the number of days between the election and the registration deadline, state level education, average turnout, average partisan performance, average registration, and the presence of Perot, they found that there was a strong link between motor voter laws and turnout in 1992. Regarding partisan bias, they found that Democrats may have benefited, but not at a statistically significant level. Brians and Grofman (1999) also studied the effects of reducing institutional barriers to voting by looking at same day voter registration over the period 1972-1992. However, they did not study partisan effects, but rather demographic effects, finding that the population that come to the polls that otherwise would not have was primarily composed of medium education, medium income voters.

On the behavioral side Brians and Wattenberg (2002) studied the partisan turnout bias of midterm elections. Looking at individual level NES data from 1978-1998 rather than aggregate level ecological data, they find that there is a significant bias against Democrats in midterm elections due to the lower turnout, because of correlations between being a registered nonvoter and having Democratic preferences. Knack (1994) also used NES data to use inclement weather to guide a natural experiment. Using presidential election data from 1984 through 1988, he finds that weather deactivates certain voters based on their "civic duty to vote." By that measure, Democrats do not have a disadvantage versus Republicans, so weather neither harms nor hinders one party or the other.

# 3 My Preliminary Results

Since it is significantly easier to obtain data aggregated to the state level, I have the most complete analyses using that data.

First, let us look at a simple OLS regression of the performance of the Democrats on turnout and some other variables and their interactions with incumbency. Specifically, the following regression is over every presidential election from 1980 to 2000 and the dependent variables are dummies for each state (not listed), the two party turnout, the two party turnout interacted with democratic incumbency, the year, incumbency, the home states of the candidates, unemployment, the change disposable income over the previous year and the next year, and the economic variables' interactions. The independent variable is the percentage of the vote accrued to the Democrats.

| Variable | $\beta$ | Standard Error | P-value |
|---|---|---|---|
| TWOPARTYTO | -.323522 | 0.061043 | [.000] |
| DTWOPARTYTO | .025724 | 0.072311 | [.722] |
| YEAR | 4.31E-03 | 7.41E-04 | [.000] |
| DEMINC | -0.088445 | 0.051744 | [.089] |
| DEMPRES | 0.069703 | 0.018903 | [.000] |
| DEMVP | 0.03351 | 0.019097 | [.081] |
| REPPRES | -0.038026 | 0.022037 | [.086] |
| REPVP | 8.58E-03 | 0.020834 | [.681] |
| UNEMPLOYMENT | .196028 | 0.226206 | [.387] |
| DUE | 0.645768 | 0.336607 | [.056] |
| PREVDISP | -0.931344 | 0.138688 | [.000] |
| DPD | 0.757418 | 0.276679 | [.007] |
| NEXTDISP | -0.290024 | 0.246867 | [.241] |
| DND | 0.124864 | 0.362243 | [.731] |
| R-squared | 0.880788 | | |
| N | 306 | | |

Notably, we can see that, by this measurement, increased turnout significantly harms Democrats at the polls, regardless of incumbency.

For our next analysis I will use temperature and precipitation as instruments. To control for regional variations, the variables I will use will be the ranking of temperature or precipitation in the state on election day in comparison to all such days in November in the last 100 years or so. First, we can see just how (very unsettling!) well temperature and precipitation predict turnout:

| Variable | $\beta$ | Standard Error | P-value |
|---|---|---|---|
| TEMP | .334442E-03 | .123554E-03 | [.007] |
| PRECIP | -.195632E-03 | .117373E-03 | [.097] |
| YEAR | -.591971E-02 | .609326E-03 | [.000] |
| UNEMPLOYMENT | -.712124 | .259383 | [.006] |
| DEMPRES | .483199E-02 | .023741 | [.839] |
| DEMVP | .017775 | .024234 | [.464] |
| REPPRES | .035893 | .027520 | [.193] |
| REPVP | .070434 | .025284 | [.006] |
| PREVDISP | .587220 | .093773 | [.000] |
| NEXTDISP | .520444 | .173874 | [.003] |
| R-squared | .661714 | | |
| N | 306 | | |

Since there is no immediate intuitive interpretation of the $\beta$'s for the weather variables, I should note that they mean that (roughly) weather accounts for about a 5-point swing in turnout.

So now that we know we have good instruments, we can get better estimates for our original regression:

| Variable | $\beta$ | Standard Error | P-value |
|---|---|---|---|
| TWOPARTYTO | -.695057 | .218977 | [.002] |
| DTWOPARTYTO | .075679 | .281907 | [.788] |
| YEAR | .195898E-02 | .156462E-02 | [.211] |
| DEMINC | -.113017 | .185442 | [.542] |
| DEMPRES | .075243 | .021019 | [.000] |
| DEMVP | .043087 | .021856 | [.049] |
| REPPRES | -.031395 | .026807 | [.242] |
| REPVP | .029181 | .030054 | [.332] |
| UNEMPLOYMENT | -.069367 | .292610 | [.813] |
| DUE | .498558 | .385006 | [.195] |
| PREVDISP | -.797317 | .196101 | [.000] |
| DPD | .807075 | .328399 | [.014] |
| NEXTDISP | .069898 | .366957 | [.849] |
| DND | -.116185 | .440634 | [.792 |
| R-squared | .859279 | | |
| N | 306 | | |

Two things are of immediate importance in this regression. First, we can see that the negative effect on Democratic performance of turnout is significantly increased. Second, some of the other variables in the regression have more reasonable t-statistics. For example, the year ceases to be significant either way, and the importance of the home states of the candidates seems to make more sense.

# 4 In the Works

I am planning several other analyses on this data once I finish cleaning up the county level data:

First, I will simply repeat the above analyses with the more detailed data. In regards to this, I will try different parametrizations of weather.

The next thing I will do is to try matching. I am hopeful that with the 3000 or so counties, this should work fairly well. The one problem becomes what to match on. To that end, I think I will match on economic statistics and baseline election results. I will also try the match with the weather data. An additional method that will be available as a result of the matching will be to compare the effect to the baseline statistics themselves. Perhaps this will elucidate what the driving force is.