The Joke Isn't on the Democrats? The Partisan Effects of Voter Turnout

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Abstract

This paper uses county-level electoral returns from the 1988-2000 presidential elections to measure the partisan effects of voter turnout. We first develop a simple theoretical model of voting to guide our analysis. We then argue that turnout is an endogenous variable to elections, so in order to obtain unbiased estimates we must use the instrumental variables estimator. In particular, we use weather as an instrument to show that voter turnout has a large and significant effect on partisan results, increasing the performance of Democrats. We then check if the effect is dependent on how partisan a county is, and find that it is not. Finally, we show that the effect does not have a meaningful trend over time. We finish by considering some implications of our findings.

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1 Introduction

According to the *Washington Post*, one Republican electoral strategy is to urge its partisans to pray for rain on Election Day.[1] According to their theory, the rainfall will suppress voter turnout, and, as a result, lead to Republican victories. Though somewhat silly, this example is emblematic of the conventional wisdom, which holds that increased voter turnout is a boon for Democrats.

The logic behind this idea is simple: For a variety of reasons, Democrats tend to be more apathetic than Republicans. As such, Democrats are less likely to vote. Thus, heavy turnout is probably caused by large number of these apathetic Democrats defying their usual ways and actually showing up at the polls.

Political scientists hold a different view on the partisan effects of voter turnout. For both theoretical and empirical reasons, there is a debate as to whether increased turnout helps Democrats, Republicans, or neither.

The purpose of this paper is to resolve this dispute. In particular, we answer the question: which party benefits from voter turnout, and how much? To answer this question, the main method we use is first differencing regression estimation with instrumental variables, in order to eliminate the endogeneity of turnout. We constrain our analyses to the presidential elections from 1988 to 2000 and consider county-level data.

In section two, we review the relevant literature. First we consider the main theoretical inroads that have been made into this problem. Second, we examine the empirical analyses that have been conducted. In this section we do not constrain ourselves by only considering presidential elections.

In section three, we develop a theoretical framework in order to allow us to analyze the problem at hand. In particular, we develop a model of the individual choice of whether or not to vote, as well as the individual choice of whom to vote for. We then

[1] This example is taken from Knack (1994).

combine these two models into one of county-level electoral returns and simplify the result to allow empirical analyses.

In section four we describe the data that we use in this project. In particular, we describe our dependent variables, our control variables, our endogenous variable, and its instruments.

In section five we offer the results of our analyses. First we give the results of naive, uninstrumented estimates of the effect of voter turnout. Second, we consider the effects of weather on both voter turnout and partisan results. Third, we offer instrumental variables estimates. These estimates show that voter turnout has a very positive effect on Democratic performance. Fourth we check if the effect changes with the partisanship of a county, finding that it does not. Finally, we show that the effect is not changing over time.

In section six, we consider some of the implications of our findings. We examine both the theoretical and practical implications.

In section seven, we conclude.

2 Literature Review

The literature on the partisan effects of voter turnout is highly polarized. Some scholars argue in favor of the conventional wisdom that turnout helps Democrats, others argue turnout helps Republicans, while a third group argues that turnout is neutral. Regardless of their stance, these arguments stem from empirical studies within the framework of the Two Effects Theory, DeNardo's (1980) seminal theoretical description of how voter turnout can have a partisan impact. Most authors have simply regressed electoral results on voter turnout in some particular sample; others, however, have conducted more nuanced analyses, using natural experiments to tease out important relations. We now review the literature relevant to this thesis: The

Two Effects Theory, other theoretical arguments, evidence on the partisan effects of turnout, and evidence from natural experiments.

2.1 The Two Effects Theory

In his seminal work, DeNardo (1980) defines a mathematical model to explain why turnout affects partisan outcomes by the means of two effects. The composition effect is driven by the existence of peripheral voters, who, because of their demographic characteristics, tend to be Democratic voters. Thus, when turnout increases, the composition of the electorate tends to be more Democratic. The defection effect is also driven by peripheral voters. Such voters tend to defect more readily than core voters and, indeed, often make the decision to vote for the same reason they decide to defect: The race is particularly divisive. Thus, since such voters are more likely to defect, high turnout means that more Democrats are defecting to the Republican side than the other way around. As a result of the existence of these two effects, it is impossible to say whether increasing turnout should help the majority party or hurt it.

2.2 Other Important Theory on the Partisan Effects of Turnout

The Two Effects Model is not the only theory about turnout's partisan effects. Tucker and Vedlitz (1986) criticize the model because it is continuous rather than binary in nature. Specifically, they claim that DeNardo's definition of what it means to have partisan effects is fundamentally flawed: He measures percentage outcomes in electoral results rather than the one variable that matters: the likelihood of winning.

Grofman, Owen, and Collet (1999) recognize the theoretical disagreements of the various camps of the debate and claim they know its cause: Each group is answering a fundamentally different question than the other, which is, importantly, not the question that either is trying to answer. One group answers the question: "Are low turnout voters more likely to vote Democratic than high turnout voters?" The second answers: "Should we expect that elections in which turnout is higher are ones in which we can expect Democrats to have done better?" Neither answers the true question: "If turnout were to have increased in some given election, would Democrats have done better?" The authors believe the answers to the first questions are yes and no, respectively. They also claim that the last question is "unanswerable absent an explicit model of why and how turnout can be expected to increase, and/or analyses of individual level panel data.

Grofman, Owen, and Collet also identify three theoretical causes for how turnout can affect elections. The "partisan bias effect" revolves around Democrats' being more likely to stay home because of demographic characteristics. The "bandwagon effect" revolves around the likelihood of peripheral voters' defecting. The "competition effect" revolves around voters being more likely to vote in close elections, which are particularly likely to arise with weak incumbents.

2.3 Evidence from House Elections

DeNardo (1980) buttresses his theory with evidence from House elections. Specifically, he obtained over 300 congressional election results from 1938 to 1966, and broke them into groups based upon the size of the Democratic electorate. For each, he regresses the Democratic share of the vote on the inverse of turnout, as necessitated by his model. For elections in 1938, 1946, 1950, and 1954, he finds that Democrats benefit from turnout where they are the minority party and suffer where they are in a strong majority. However, in 1962 and 1966, the pattern terminates. DeNardo interprets his results to be the result of an ever shrinking population of core voters.

2.4 Evidence from Senatorial and Gubernatorial Elections

Nagel and McNulty (1996) hold that the best way to measure the effects of voter turnout is to look at senatorial and gubernatorial elections. House data is insufficient because districts are redrawn every ten years and are often extremely uncompetitive. On the other hand, national-level presidential data is too sparse, while state-level data causes statistical difficulties as observations are not independent. Using a variety of statistical models (most notably least squares with dummy variables for the state effects), they affirm DeNardo's theory, showing in their sample and with their methods, that from 1928 to 1964 turnout helped Democrats, but thereafter the relationship vanished.

2.5 Evidence from Presidential Elections

Beginning with DeNardo, (1980) many scholars have sought to determine the empirical relationship between turnout and the partisan vote for president. Critics quickly debunked DeNardo's (1980) work 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 uses two major methodologies. In one, he simply pools 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) claims that Radcliff's research merely depicts the impact of the voting rights revolution in the South. Controlling for this factor, the relationship disappears.

Seeking to resolve the disagreement of their senatorial and gubernatorial data (1996) with Radcliff's (1994a) data, Nagel and McNulty (2000) regress 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 or other temporal variation.

2.6 Natural Experiments

Though they have not explicitly tested turnout relationships through the use of two staged least squares analysis, several authors have attempted to use natural experiments to unravel the relationship. These experiments fall into two natural categories, examinations of institutional barriers to voting and examinations of behavioral reasons for not voting.

Franklin and Grier (1997) examine 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 find that there was a strong link between motor voter laws and turnout in 1992. Regarding partisan bias, they find that Democrats may have benefited, but not at a statistically significant level. Brians and Grofman (1999) also study the effects of reducing institutional barriers to voting by looking at same day voter registration over the period 1972-1992. However, they do not study partisan effects, but rather demographic effects, finding that the population that comes to the polls that otherwise would not have is primarily composed of medium education, medium income voters.

On the behavioral side Brians and Wattenberg (2002) study the partisan turnout bias of midterm elections. Looking at individual level National Election Studies 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 uses National Election Studies 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 A Simple Model of Voting

Before we can turn to the main topic of this paper–empirically measuring the partisan effect of voter turnout–we must develop a simple model of voting to guide our studies. In this section, we first define a model of the decision of whether or not to vote. Second, we define a model of the partisan decision of whom to vote for. Third, we combine the models into a complete model of electoral results. Finally, we simplify the model to allow for empirical analysis.

Before proceeding, we should note that for the sake of simplicity, we model the two decisions as binary decisions. First the voter chooses whether or not to go to the polls, and then the voter chooses whether to cast his ballot for either the Democrat or the Republican. Defining the decisions like this, of course, denies the possibility of voting for a third party. However, since third parties have never been viable in the period this analysis considers, we define a vote for a third party as a non-vote. That is, a voter who does not vote for a Democrat or a Republican is considered to have not voted at all.

3.1 The Decision to Vote

We model the decision of whether or not to vote as a rational decision. Specifically, voters choose to vote if their personal benefit for a given election is less than their personal cost for a given election. So for agent i to choose to vote in election t the following inequality must hold:

$$B_{it} - C_{it} > 0, \tag{1}$$

where B_{it} and C_{it} are the benefit and cost of voting, respectively.

We model the benefit of voting as having two components. First, each agent has an individual benefit from voting b_i, which is time invariant. Second, there are environmental factors that impact whether or not a voter chooses to vote. These factors can come in many forms. For the sake of the model, we define them as being of two main types, exogenous and endogenous. The exogenous factors include economic variables and political variables that political parties (for the purposes of the model) are unable to influence. These variables could operate in a variety of ways. For example, poor economic conditions could mobilize voters or, alternatively cause voters to feel disenfranchised and stay home. Alternatively, certain candidate characteristics could energize voters to go to the polls or turn voters off. Regardless we group all of these exogenous variable in the vector $\vec{x}_t$.

Endogenous variables include all variables which political parties are able to influence. They include get-out-the-vote efforts, which are intended to mobilize voters, advertising, which can either mobilize or demobilize voters, and other such measures of political effort in a district. This group of variables also includes variables that are not controlled by any agents, but are nonetheless endogenous to the full voting system. One such variable that springs to mind is the closeness of the election. As the expected margin of victory increases, voters are, rationally, less likely to vote. We group all endogenous variables in the vector $\vec{z}_t$.

Thus we model the benefit to voting with the following function:

$$B_{it} = b_i + f(\vec{x}_t, \vec{z}_t), \tag{2}$$

where f is a function that maps the exogenous and endogenous variables to an impact on the benefit of voting.

As with the benefits of voting, we model the costs of voting as having two components. As before, each agent has a time invariant cost of voting, c_i. However, since both b_i and c_i are time invariant, we can set:

$$c_i = 0, \tag{3}$$

without any loss of generality. The second component contains the environmental variables that affect the cost of voting. Many of these variables could be included in $\vec{x}_t$ and $\vec{z}_t$, however, by the same argument we used with the time invariant costs, we can include any of these costs in f. The costs of voting, however, take a third argument, $\vec{w}_t$, which for analysis contains variables reflecting the weather. As the weather gets worse, people are less likely to vote, thus the costs of voting becomes:

$$C_{it} = g(\vec{w}_t), \tag{4}$$

where g maps the weather to the cost of voting. For full generality, the vector $\vec{w}_t$ could contain other variable, such as the ease of registration.

Putting the benefit and cost of voting together, we obtain that agent i votes if the following inequality holds:

$$b_i + f(\vec{x}_t, \vec{z}_t) - g(\vec{w}_t) > 0. \tag{5}$$

3.2 The Partisan Decision

We model the partisan decision to vote for an individual with the same framework we used to model the decision to go to the voting booth. In particular, agent i votes for the Democratic Party if the following inequality holds:

$$a_i + h(\vec{x}_t, \vec{z}_t) > 0. \tag{6}$$

Here a_i represents the agent's individual propensity to vote for the Democratic Party, and it analogous to the variable b_i. The function h takes as arguments the same exogenous and endogenous variables as went into the decision to vote at all. In that case, exogenous and endogenous variables serve to either mobilize or demobilize voters. In this case, these variables serve to influence people to vote one way or the other.

3.3 Putting the Two Frameworks Together

The unit of analysis in this paper will be the county. Thus, we must determine how to combine the two simple models above into a model of county-level electoral results. Before proceeding we should note that the following analysis is relevant to a given county. Thus, all variables and functions should technically be subscripted by the county. However, to avoid unnecessary notational complexity, we drop all such subscripts.

We now turn to some necessary assumptions. First we assume that, in a given county, the following variables are the same for every voter: $\vec{x}_t$, $\vec{z}_t$, and $\vec{w}_t$. Such an assumption is warranted because we define these variables as environmental variables, which should be constant in a given county. We make the somewhat more restrictive assumption that f, g, and h are the same for every voter as well. Finally, we assume that the composition of counties in terms of baseline propensities to vote and vote Democratically are time invariant. This is, of course, very restrictive, but it makes the analysis much simpler. For technical reasons, we assume that the values of b_i and a_i are continuously distributed in a given county. Thus, instead of knowing the number of people with values of b_i or a_i equal to a given value, we simply know the density of such people.

With these assumptions, it makes sense to define the joint distribution $p(b, a)$, which is the density of people with baseline voting tendency b and Democratic tendency a. Thus total number of voters in a county is given by the following integral:

$$n = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(b, a) da db. \tag{7}$$

Since people vote if and only if the following inequality holds:

$$b_i > g(\vec{w}_t) - f(\vec{x}_t, \vec{z}_t), \tag{8}$$

we can see that the voter turnout will be given by:

$$T_t = \frac{1}{n} \int_{g(\vec{w}_t)-f(\vec{x}_t,\vec{z}_t)}^{\infty} \int_{-\infty}^{\infty} p(b, a) da db. \tag{9}$$

Since people vote for the democratic party if and only if the following two inequalities hold:

$$b_i > g(\vec{w}_t) - f(\vec{x}_t, \vec{z}_t) \tag{10}$$

$$a_i > -h(\vec{x}_t, \vec{z}_t), \tag{11}$$

the percentage of the two-party vote accruing to the Democratic Party is given by:

$$\frac{D_t}{T_t} = \frac{1}{T_t} \int_{g(\vec{w}_t)-f(\vec{x}_t,\vec{z}_t)}^{\infty} \int_{-h(\vec{x}_t,\vec{z}_t)}^{\infty} p(b, a) da db. \tag{12}$$

3.4 Simplifying the Model for Empirical Analysis

The above model will be unwieldy for the purposes of empirical analysis. To simplify the model, we assume that the function g is linear in its arguments. Thus the function is given by:

$$g(\vec{w}_t) = \vec{\omega}_w \cdot \vec{w}_t \tag{13}$$

where $\vec{\omega}_w$ is a constant vector of the appropriate length.

We are now equipped to define some derivatives of interest. In particular, the derivative of voter turnout with respect to a given weather variable w_{tj} is given by:

$$\frac{\partial T_t}{\partial w_{tj}} = \frac{-\omega_{wj}}{n} \int_{-\infty}^{\infty} p(g(\vec{w}_t) - f(\vec{x}_t, \vec{z}_t), a) da. \tag{14}$$

This derivative has a simple interpretation. The effect on turnout of a small change in a weather variable is precisely equal to the derivative of the cost function (defined negatively) times the density of voters who are on the margin as to whether or not to vote.

We can also define the main value of interest–the derivative of Democratic vote share with respect to turnout. In this case, we have:

$$\frac{\partial}{\partial T_t}\left(\frac{D_t}{T_t}\right) = \frac{\frac{\partial D_t}{\partial T_t} T_t - D_t}{T_t^2}. \tag{15}$$

If we instead differentiate with respect to the natural logarithm of turnout we obtain:

$$\frac{\partial}{\partial \ln T_t}\left(\frac{D_t}{T_t}\right) = \frac{\partial D_t}{\partial T_t} - \frac{D_t}{T_t}. \tag{16}$$

Finally, if we differentiate the logarithm of Democratic vote share with respect to the logarithm of turnout we obtain:

$$\frac{\partial}{\partial \ln T_t} \ln\left(\frac{D_t}{T_t}\right) = \frac{\partial D_t}{\partial T_t}\frac{T_t}{D_t} - 1. \tag{17}$$

Of course, all three of these derivatives still have the term $\frac{\partial D_t}{\partial T_t}$ in them. In practice we will be controlling for the variables in $\vec{x}_t$ and not considering $\vec{z}_t$ because those are endogenous variables. In addition, controlling for all but one element of $\vec{w}_t$, we can thus obtain the derivative:

$$\frac{\partial D_t}{\partial T_t} = \frac{\partial D_t}{\partial w_{tj}}\frac{\partial w_{tj}}{\partial T_t} \tag{18}$$

$$= \frac{\int_{-h(\vec{x}_t,\vec{z}_t)}^{\infty} p(g(\vec{w}_t) - f(\vec{x}_t,\vec{z}_t), a)da}{\int_{-\infty}^{\infty} p(g(\vec{w}_t) - f(\vec{x}_t,\vec{z}_t), a)da}. \tag{19}$$

This derivative also has a very simple interpretation: It is the percentage of voters who vote Democratically of those who are just on the margin.

In the empirical analysis that follows we will be considering many different counties across the country. However, we will want some way of determining $\frac{\partial D_t}{\partial T_t}$ for all counties. To that end, there are two natural ways to define this value. One way is to set:

$$\frac{\partial D_t}{\partial T_t} = \frac{D_t}{T_t} + \beta. \tag{20}$$

Making this assumption is equivalent to assuming that the proportion of marginal voters who will vote Democratically in a given county is equal to the percentage of Democratic voters in that county, plus some premium β. In other words, if $\beta = .1$, then if a district gives sixty percent of its votes to the Democratic Party, we can assume that its marginal voters will be voting for the Democratic Party at a rate of seventy percent. Furthermore, as we will see later, making this assumption makes it very logical to regress the Democratic vote share on the natural logarithm of voter turnout because then one obtains:

$$
\begin{aligned}
\frac{\partial}{\partial \ln T_t}\left(\frac{D_t}{T_t}\right) &= \frac{\partial D_t}{\partial T_t} - \frac{D_t}{T_t} && (21)\\
&= \frac{D_t}{T_t} + \beta - \frac{D_t}{T_t} && (22)\\
&= \beta. && (23)
\end{aligned}
$$

So the regression coefficient in this case is simply the difference between how Democratic a county's marginal voters and regular voters are.

Another natural way to define the proportion of marginal Democratic voters is to set:

$$\frac{\partial D_t}{\partial T_t} = (1+\alpha)\frac{D_t}{T_t}. \qquad (24)$$

In this case, α is also a parameter measuring how much more Democratic marginal voters are than regular voters. However, in this case, the effect is proportional. So if $\alpha = .1$ and a district is sixty percent Democratic, we expect the marginal voters in that district to be sixty-six percent Democratic. As before, this assumption gives a logical regression. In this case, regressing the logarithm of the Democratic vote share on the logarithm of the turnout gives:

$$
\begin{aligned}
\frac{\partial}{\partial \ln T_t}\ln\left(\frac{D_t}{T_t}\right) &= \frac{\partial D_t}{\partial T_t}\frac{T_t}{D_t} - 1 && (25)\\
&= (1+\alpha)\frac{D_t}{T_t}\frac{T_t}{D_t} - 1 && (26)\\
&= \alpha. && (27)
\end{aligned}
$$

So in this case, the regression coefficient is the percentage difference between how Democratic a county's marginal voters are versus their consistent voters.

4 Data

We now turn to considering the data to be analyzed in this paper. We first consider the data on electoral outcomes. Second, we consider the political and economic data used as control variables. Finally, we consider the weather data. In each section, we justify our choice of specific data series, identify its role in the model, and describe how it was obtained or created.

4.1 Poll Data

Because this is a paper about the partisan effects of voter turnout, the most important data are the numbers on both voter turnout and partisan results. While partisan results are easy to obtain, voter turnout statistics can be quite problematic. While some states make county or even precinct level turnout data available, they are the exception to the rule. If one wants to consider the entire United States, the best data available at a reasonable level of aggregation is that produced by Election Data Services. In particular, they provide data on voter turnout for every national election since 1988 on the county level for almost every state. Because this analysis only considers presidential elections, this analysis is constrained to looking at just four elections, those of 1988, 1992, 1996, and 2000.

Before proceeding, we justify our choice to consider data on the county level. Turnout data is available on the state level over a much longer time frame. However, this aggregation is problematic for several reasons. Most importantly, for the purposes of this study, thinking about weather on a state level makes little sense. The temperature in Northern California is almost certainly not the same as the temperature in Southern California. However, though it might still be false, it is reasonable to assume that weather is constant throughout Santa Clara County. Furthermore, only looking at state level data washes away much of the variation in economic variables that we know to be of the utmost importance in determining election outcomes.

Another option would be consider data on an individual level, using the National Election Studies data, for example. This approach, however, is problematic for two reasons. First, voter turnout is a notoriously misreported statistic in such studies. People simply lie about whether or not they voted. Such error could very well be correlated with other covariates and would thus bias the results of the analysis. On a more fundamental level, aggregating the data makes sense intuitively in this analysis. When we are studying electoral results, the primary outcome of interest is indeed the aggregated result. So if there are multiple, counteracting effects of which one is just barely stronger, this is of high importance. Such an effect would show up when looking at aggregate data, but might not when looking at individual data.

Regardless of the merits of using county-level data, doing so is a choice we have made in this paper. To that end, we now turn to defining the variables we have obtained from Election Data Services.

4.1.1 Democratic Vote Share: *DemPer* or ln(*DemPer*)

The dependent variable in most regressions will be *DemPer*. This variable is simply the number of Democratic votes in a county divided by the number of votes for either major party. Similarly, ln(*DemPer*) is simply the natural logarithm of *DemPer*. This variable is used as the dependent variable in some regressions as well.

The one possibly controversial choice we make in regards to these two variables is defining them as Democratic performance in a district relative to just the Republican Party. As a result, we disregard third parties. The reason we care about Democratic performance in a county is that it affects whether or not the Democrats win that state, which in turn affects their chances at winning the national election. To that end, during the period in question, there are only two parties in contention at the state level. Thus, it only really makes sense to consider the two-party vote share.

4.1.2 Voter Turnout: ln(*Turnout*)

The primary variable of interest, voter turnout, is endogenous. As we discussed above, this variable is endogenous for several reasons. First, turnout decreases when elections become less close. Second, parties, in their interactions with voters, strategically choose districts in which they will focus their efforts to mobilize or demobilize voters. These efforts, however, are endogenous to how well the party is expected to perform in the district. Regardless of its endogeneity, voter turnout is the key explanatory variable in this analysis.

We measure voter turnout by taking the logarithm of the total number of votes for either major party divided by the number of registered voters. In states which do not require registration, we use the voting age population, as every voter is, for all intents and purposes, registered. We choose to measure the two-party turnout to be consistent with our choice for how to measure Democratic performance. We choose to take the logarithm because that is the theoretically relevant variable.

Here we should note that the available data limits the sample size. Specifically, Election Data Services does not provide either registration numbers or voting age population statistics for three states: Alaska, North Dakota, and Wisconsin. Thus these states are excluded from the sample. As a result, we are left to analyze the 2,987 remaining counties that are spread across the United States, leaving us with a total of 11,948 observations.

4.1.3 County Weights

As we have stated before, the reason we care about the effect of voter turnout on Democratic performance is that it could influence election results. To that end, not all counties are created equally. Large counties are more important to the analysis for two reasons. First, they contain more people, so they affect statewide returns to a larger extent. Secondly, they are aggregations over a larger number of people, so, from a statistical perspective, they are more important. Regardless, it is natural to weight counties by their population.

Of course, population could mean many things. It could refer to the actual population of the county; it could refer to the voting age population, it could refer to the number of registered voters; or it could refer to the number of votes cast for a major party. Because the dependent variable is Democratic Party, we weight by the number of votes cast for a major party. This method makes sense under either reason for weighting the counties.

Because we use panel data methods, notably fixed effects and first differencing, it is important that a given county has the same weight in each election in order for the estimators to be unbiased and efficient. Thus we choose for the weight of county i the following statistic:

$$\gamma_i = \sum_t \frac{T_{it} * n_{it}}{\sum_j T_{jt} * n_{jt}}. \tag{28}$$

The quantity inside the outer summation is simply the proportion of votes in a given year from county i. The summation simply adds up this proportion for each of the four elections in our sample. To fix ideas, suppose that a county produces 5%, 6%, 3%, and 4% of the national vote in the four years we study. Then its weight will be simply .18. Thus the total of all the weights will add up to 4.

Before proceeding we should note that all regressions in this paper are weighted using this method.

4.2 Political and Economic Data

We now turn to considering the primary exogenous variables. In our theoretical framework, these are the variables that make up the vector $\vec{x}$. In particular, we consider three main classes of variables for this category: economic conditions in a county, candidate characteristics, and temporal variables. We begin with the economic variables.

4.2.1 Per Capita Income: ln(*Income*) and $D\times$ln(*Income*)

One important economic control variable is per capita income. In particular, we obtained from the Bureau of Economic Analysis the per capita income for every county in the United States. We define two variables with the measure. First, we define $\ln(Income)$ as the natural logarithm of per capita income in a county. Second, we define $D\times\ln(Income)$ as the same natural logarithm interacted with whether or not the incumbent is a Democrat. This value equals zero if the president is a Democrat.

Importantly, we should note that our data for per capita income does not account for inflation. This is done because local inflation statistics are unavailable, so there would not be an unbiased measure of inflation. For example, a measure of inflation that includes housing prices would measure inflation more accurately for big cities, where such prices are in flux. However, applying this measure to rural counties would then consistently underestimate that county's real income. Because being a rural versus urban county is correlated with being Republican versus Democratic, applying an untrue measure of inflation would bias the results.

One potential concern with not accounting for inflation is that then the value of $\ln(Income)$ will almost certainly be increasing over time. However, as we will see later in this section, we allow temporal variables, so any effect artificially created by inflation will be washed away with those variables.

However, because we cannot account for inflation, it makes more sense to use the natural logarithm of per capita income than to simply use per capita income. Without taking the natural logarithm, changes in real per capita income will appear larger as time goes on. For example, suppose the rate of inflation is 10%, and one county has a per capita income of \$100 while another has a per capita income of \$200 in the first year. Assuming nothing real changes, in the second year, the incomes will be \$110 and \$220. Thus the difference will appear to have increased by \$10.

Now suppose we use the natural logarithm of income. Then in the first year the two values will be ln(100) and ln(200). The difference in these two values is given by the definition of the logarithm as ln(2). In the second year, the two values will be ln(110) and ln(220). By the definition of the logarithm, the difference between these two functions is also ln(2). Thus, it is more prudent to use the logarithm of income than simply per capita income.

Finally, by the model of retrospective voting, we must include both per capita income and the interaction of per capita income with incumbency in any regression. This allows voters to reward incumbents for economic growth and punish them for poor performance. It goes without saying that D×ln(income) is the same as ln(income) in 1996 and 2000, and equal to zero in 1988 and 1992.

4.2.2 Economic Growth: *Change* and $D\times$*Change*

The other economic control variable we use is the percentage change in per capita income over the year leading up to the election. This data was, as before, obtained from the Bureau of Economic Analysis. Similarly with the previous case, we define two variables: *Change*, the percentage change in per capita income over the previous year, and $D\times$*Change*, the interaction with the incumbency of the president.

As before, we should note that per capita income is measured nominally. In this case, however, this situation should not pose much of a problem , because *Change* is already measured as a percentage. Of course, such a measure does mean that growth will appear larger than it actually is by exactly the value of inflation. However, because temporal variables are included, this should not cause a bias.

The justification for using both *Change* and $D\times$*Change* is the same as with $\ln(Income)$ and $D\times\ln(Income)$.

4.2.3 Candidate Characteristics: ***DemPres***, ***DemVP***, ***RepPres***, and ***RepVP***

We now turn to considering the political variables in the model. Most political variables that can be easily measured are national, not local. One variable, however, is decidedly local and very easy to measure: candidates' home state. To that end, we include four variables in our regressions: *DemPres*, *DemVP*, *RepPres*, and *RepVP*. These variables equal 1 in the home state of the Democratic presidential nominee, Democratic vice-presidential nominee, Republican presidential nominee, and Republican vice-presidential nominee, respectively. In all other states they equal zero. Thus, these variables allow candidates to perform better in their home states.

4.2.4 Temporal Variables: ***Year1988***, ***Year1992***, ***Year1996***, and ***Year2000***

The final set of exogenous variables we include are dummy variables for each year: *Year1988*, *Year1992*, *Year1996*, and *Year2000*. Including these variables has tremendous power. They control for all variables that are effective nationally. Thus any particular issues in the election, any particular candidate traits that are affecting the decisions of voters, or any national economic trends will be controlled for by these four variables. In short, these variables control for much of the variation in unobservable variables, insofar as they are national-level.

4.3 Weather Data

We now turn to considering the instrumental variables we use in this study. All instrumental variables are weather-related and drawn from the Daily Surface Data of the National Climactic Data Center. As the methodology for gathering each variable was the same, it is worth considering how each particular observation was obtained before proceeding to specifically describe each variable.

In particular, weather data from 482 national weather stations was obtained. Additionally, we obtained the longitude and latitude of each station. We also obtained the longitude and latitude of the center of each county in the United States. We then simply matched each county to its closest weather station to obtain weather data for that county.

There are 2,987 counties in our sample, so there are clearly too few weather stations. Worse still, some of the stations are in counties that have been dropped from the sample for other reasons and many of the stations appear in clusters, because oftentimes large counties have more than one station. As we consider each variable, we will consider the potential errors introduced by using weather in nearby counties.

We now describe all six of our weather variables, first considering temperature variables, then concerning precipitation variables, and finally snowfall variables.

4.3.1 Temperature: ***MaxTemp*** and ***MinTemp***

The first two weather variables we consider are the maximum and minimum temperature recorded in a county on a particular day. These two variables are denoted by *MaxTemp* and *MinTemp*, respectively. Both of these variables are measured in degrees Fahrenheit.

According to Knack (1994), temperatures in neighboring counties are usually very similar. Thus, according to his logic, no error is introduced by only having the temperature for the nearest station.

One potential bias that could be introduced by this measure is that temperature varies regionally, as does partisanship. In particular, the Sun Belt is peculiarly warm as well as conservative. However, when we use fixed effects or first differencing, this bias disappears.

The bias that does not disappear is that of variability. In particular, certain regions may have more or less variability in temperature than others. However, because the mean deviation from the average is zero in every county, we conclude that such variation in variance does not produce a bias, though it may lead to inefficient estimators.

Finally, we note that maximum temperature is probably a much better instrument than minimum temperature. Most voting occurs during the day, which is also when the maximum temperature occurs. The minimum temperature, on the other hand, occurs, usually, before or after the polls close.

For the above reasons, we believe that maximum temperature is the best instrument available.

4.3.2 Inclement Weather: ***Precipitation*** and ***Rained***

We also have data for inclement weather. In particular, *Precipitation* equals the total hundredths inches of either rainfall or snowfall in a given county. *Rained* is a dummy variable, which equals one if there is any precipitation and zero otherwise.

Unlike temperature, which is very smooth geographically, precipitation can often have local variation. Thus it is somewhat less precise a measure than temperature. However, it is hard to imagine that this situation can create very large measurement error, as precipitation is a roughly smooth function as well. As for the dummy variable indicating whether or not it is raining, it is hard to say how the error may behave. On the one hand, if it is raining in neighboring counties, then there will be no error in the measurement. However, if it is raining in one county, but not another, the error will be very much present.

As with temperature, we might have reason to be concerned that certain regions that always have more precipitation are more liberal. However, this bias goes away if fixed effects or first differencing is used. As to the variability being regional, this is a concern here as well, but we conclude that it is not important for the same reasons as before.

One very important note of caution with these weather data series is that there are, almost assuredly errors. In particular, one county in Hawaii measures rainfall at 4.51 inches, which is rather unreasonable. However, because there are also errors on the other end that are more difficult to identify, we do not consider the effects of dropping observations with extreme measures. However, we should note again that such data causes concern that there are pervasive errors in this data series.

Finally, we should justify including both *Precipitation* and *Rained* as explanatory variables. Doing so allows just a miniscule amount of rain to have a disproportionately large effect on voter turnout. It also allows the effect to increase with total rainfall. Such an effect seems reasonable.

4.3.3 Did it Snow?: ***Snowfall*** and ***Snowed***

The final variables included in our analysis are *Snowfall* and *Snowed*, which correspond to the total hundredths inches of snowfall and a dummy variable as to whether or not it snowed.

The analysis of these two variables is very similar to the analysis of *Precipitation* and *Rained*. In particular, the errors induced by not having accurate data for every county are substantial but not overly so. Variability may be causing a bias, but probably not. And both variables are needed to allow for the first bit of snow to be disproportionately effective in deactivating voters.

5 Results

We now report the results of the various empirical analyses conducted for this paper. All analyses are for every county in the United States, with the exception of Alaska, North Dakota, and Wisconsin, and all analyses are for the presidential elections of 1988, 1992, 1996, and 2000.

In this section, we first regress Democratic performance on all of the control variables, in order to guarantee that these variables are behaving as they should. Second, we estimate the effect of voter turnout without taking into account the endogeneity of turnout. Third, we find an unbiased estimate of the partisan effects of voter turnout by instrumenting turnout with weather variables. Fourth, we consider if the effect is different in different districts based upon their baseline partisanship. Finally, we consider whether the effect is changing over time.

5.1 Predicting Democratic Performance without Turnout

We begin our empirical analyses by considering the relationships of the control variables to the primary independent variable of interest, the two-party vote share of the Democrats. From this examination we hope to gain two insights: First, we hope to confirm that the control variables behave as expected in this data set. Second, we hope to determine and justify a choice of methodology. In particular, we consider three methodologies in this section: pooled ordinary least squares, panel fixed effects, and panel first differencing. The results of regressing the two-party vote share of the Democrats on the economic variables, political variables, and temporal variables are given in Table 1. At this juncture it is worthwhile to repeat that all regressions reported in this paper are weighted by the formula given in Equation 28.

The three different regression technologies give substantially different coefficients for each variable, so it is clear that the method used is very important to the final results. In order to determine which technology is the best, we consider the three choices in turn, discussing what may be causing biases in the estimates, then concluding that first differencing estimator provides is the best because it is unbiased.

Using pooled ordinary least squares to estimate the effects of the control variables on the Democratic two-party vote share has one major advantage over other techniques: In many applications, ordinary least squares is simply the standard. However, in this application, ordinary least squares gives qualitatively incorrect estimates for several variables. We now consider the effects of the main variables.

	Pooled OLS	Fixed Effects	First Differencing
Change	-.0094283	-.0591339	-.0463921
	(.0608771)	(.0202034)	(.0163448)
$D\times Change$	-.1035508	.1703344	.0609678
	(.0646945)	(.0225473)	(.0180815)
$\ln(Income)$	.0544516	-.2318471	-.0619873
	(.0061244)	(.0084374)	(.0086269)
$D\times\ln(Income)$	.0927617	.1086581	.0438314
	(.0084098)	(.0024945)	(.0027877)
DemPres	.0470241	.027406	.0391487
	(.0081682)	(.0028875)	(.0027193)
DemVP	.0295218	.0452827	.0330948
	(.0067086)	(.0022739)	(.0020472)
RepPres	-.0736424	-.0222067	-.0197678
	(.0052605)	(.0026998)	(.0018184)
RepVP	.0265612	.0087712	.0132739
	(.0062405)	(.0022167)	(.0017229)
Year1988	-.0735721	.9492465	.3659294
	(.059081)	(.0243553)	(.0278482)
Year1992	-.0053997	1.070304	.4551779
	(.0603814)	(.0247091)	(.0280153)
Year1996	-.9311366	.0178623	.0359023
	(.0576006)	(.0016095)	(.0015878)
Year2000	-.9922476	-	-
	(.0586189)		

Table 1: Predicting Democratic Vote Share without Turnout

Ordinary least squares shows the effect of the change in per capita income as being statistically insignificant. While a strict interpretation of the theory of retrospective voting would imply that this effect should be negative, it is possible to imagine that there is some effect which causes voters to become more Democratic as the rate of growth increases, regardless of incumbency. Thus, though it may be a little surprising, the effect shown could be theoretically consistent. However, the effect of $D \times Change$ is shown to be negative and statistically significant. If true, this effect would imply that incumbents perform better if there were poor economic growth. Such an effect is, of course, theoretically troubling.

The method also gives positive signs to both $\ln(Income)$ and $D \times \ln(Income)$. Such an effect could be theoretically consistent if one believed that higher per capita incomes made people more Democratic, but that people nonetheless voted retrospectively. To some extent, such an explanation is true. However, as we will see in a moment, this interpretation, though it captures a true effect, does not capture the one we are after.

Finally, the method gives qualitatively correct estimates for all home state variables, with the exception of the one representing the home state of the Republican presidential candidate. As this prediction is consistent across all regressions in this section, we save the discussion of this effect for later.

So why does ordinary least squares produce theoretically inconsistent results? The answer is simple: The method does not allow for county-level effects. In particular, we know for sure that counties vary widely. Some are very liberal while others are conservative. In order for the ordinary least squares estimators to be unbiased, such partisan leanings would have to be uncorrelated with any of the explanatory variables. However, we know that partisan leanings are, almost certainly, a function of local economic conditions. Thus, the coefficients for those four variables are biased. In particular, this bias explains the effect of $\ln(Income)$. In the United States, richer counties tend to be more liberal. Thus the positive coefficient on $\ln(Income)$ is not measuring a true causal effect between the economic variable and electoral results. Rather, it is simply measuring the correlation between wealthy counties and liberal counties. While this is an interesting relationship, it is not the one we are interested in, as we are interested in the political effects of imparting additional wealth into a given county.

One potential way to account for the bias of county variation is to estimate the effects with the fixed effects estimator. Doing so allows each county to have its own intercept in the regression equation. The technique, however, does assume that changes in the explanatory variables affect all counties equally.

The fixed effects estimator gives qualitatively correct estimates for all variables, with the exception of the home state of the Republican presidential nominee. The probable reason for this anomaly is the peculiar nature of this variable during the short time series available. In particular, the home state of the Republican presidential nominee is Texas in 1988, 1992, and 2000. The home state is Kansas in 1996. Since the regression is weighted by votes cast, the weight on the Texan observations will be much larger. Since this is a fixed effect regression that includes the year as a control variable as well, then, one potential explanation for this variable's having the wrong sign is that Bob Dole performed better than average in Texas, compared with his vote share other states. This explanation seems entirely reasonable.

The problem with the fixed effects estimator is that it is inefficient in the presence of serially correlated errors. In other words, the technique performs poorly when a shock in one year propagates through subsequent years. Such shocks are very likely to occur in this case. For example, suppose Southern California experienced an influx of liberal Latino voters between 1988 and 1992. Then not only would these voters affect the outcome of the 1992 election, but they would continue to affect the outcomes of future elections. Under such serially correlated errors, the first differencing estimator is more efficient (Wooldridge, 2003). Since such shocks are the norm in politics, we thus conclude that the first differencing estimator is the best estimator available.

With the first differencing estimator, all effects, with the exception of the home state of the Republican presidential nominee are both highly significant and theoretically correct. We thus proceed with the confidence that we have chosen the correct estimator.

5.2 Predicting Democratic Performance with Uninstrumented Turnout

We now turn to considering some naive estimates of the effect of voter turnout on partisan electoral results. Because one of the goals of this paper is to debunk such results, we report the results of three analyses in this section: those given by the use of pooled ordinary least squares, those given by fixed effects, and those given by first differencing. For all three of these regressions, turnout is not instrumented. These regressions are reported in Table 2.

The ordinary least squares estimate–the least sophisticated one given–shows a very significant effect of voter turnout. Indeed, the t-statistic is given as -23.7477. Such a significant effect is very rare in political science, and, in and of itself, might cause one to pause with concern. Regardless, the estimate gives the effect of voter turnout as being decidedly biased against the Democratic Party. This result is consistent with those who argue that, contrary to conventional wisdom, Republicans benefit the most from higher turnout.

Regardless of the potential endogeneity of turnout, the ordinary least squares estimate is fatally flawed because it measures the wrong effect. In particular, it simply measures the fact that counties that have consistently high turnout tend to be counties that vote Republican consistently. This is indeed an interesting relationship, but it is irrelevant to the task at hand, as it sheds no light on the question of whether

	Pooled OLS	Fixed Effects	First Differencing
ln(*Turnout*)	-.2410795	-.0285584	-.00074
	(.0101517)	(.0047194)	(.0041703)
Change	-.0762104	-.0555935	-.0464866
	(.0595568)	(.0201718)	(.0163544)
$D\times Change$	-.0763301	.1643665	.0610097
	(.0632312)	(.0225242)	(.018084)
ln(*Income*)	.0925541	-.2288441	-.0619132
	(.0061962)	(.0084353)	(.0086375)
$D\times\ln(Income)$	.0886384	.1084221	.0438348
	(.0082201)	(.0024899)	(.0027879)
DemPres	.0636637	.0293447	.0392071
	(.0080129)	(.0028995)	(.0027393)
DemVP	.0454388	.047505	.0331267
	(.00659)	(.0022989)	(.0020552)
RepPres	-.1007676	-.0211834	-.0197405
	(.0052661)	(.0026997)	(.0018251)
RepVP	.0233735	.0091553	.0132684
	(.0060998)	(.0022132)	(.0017233)
Year1988	-.5257146	.9513263	.3660937
	(.0607935)	(.0243094)	(.0278651)
Year1992	-.4972437	1.068194	.45523
	(.0625353)	(.0246625)	(.0280183)
Year1996	-1.402962	.0164265	.0358676
	(.0596921)	(.0016238)	(.0015999)
Year2000	-1.4523	-	-
	(.0596921)		

Table 2: Predicting Democratic Vote Share with Uninstrumented Turnout

or not Democrats will do well if turnout is high.

The fixed effects estimator does not suffer from this flaw. As a result the effect of voter turnout it measures is significantly attenuated. However, this estimator still measures a negative and significant effect of voter turnout on Democratic performance.

Finally, the first differencing estimator gives a statistically insignificant effect of voter turnout. As before, we prefer the first differencing estimator to the fixed effects estimator. In particular, it is very reasonable to imagine that there would be a shock that would permanently shift both a county's partisanship and its tendency to have high or low turnout. In the presence of such shocks, the first differencing estimator is superior to the fixed effects estimator. For this reason, we only consider the first differencing estimator for the rest of the analysis.

5.3 Using Weather as an Instrument for Turnout

Turnout is, of course, an endogenous variable to the electoral process. We have already discussed this factor, but to briefly reprise our discussion, turnout is endogenous for two main reasons. First, potential voters are more likely to cast ballots when elections are close. Second, political parties are more likely to try to mobilize voters in counties where doing so will have a positive effect for them. Similarly, parties will campaign harder in counties which possess larger turnout. Regardless, the endogeneity of turnout causes many problems for any statistical analysis, as it means that one of the crucial assumptions is violated. As a result, the estimates are most likely biased.

To account for this endogeneity, we use the instrumental variables. In particular, we use variables describing the weather, including temperature, rainfall, and snowfall.

In this section, we first show that weather is indeed a good predictor of turnout. Second, we directly regress partisan results on the weather. Third, we argue that the instrumental variables estimator will be unbiased. Fourth, we consider the results of the actual instrumental variables regression. Finally, we consider what difference using the natural logarithm of Democratic performance might make. For all regressions we consider using both all instruments, as well as just using the best instrument, maximum temperature. As always, all regressions are weighted by county size and contain all 2,987 counties in the sample for the years 1988, 1992, 1996, and 2000.

5.3.1 How good is Weather as an Instrument?

One potential hiccup in using instrumental variables to estimate the true effect of voter turnout on partisan performance is finding a good instrument. We now show that weather is indeed a good instrument for voter turnout. Table 3 gives the results of regressing the natural logarithm of voter turnout on all six weather variables and just maximum temperature.

Because it is simpler, we first examine the regression with only the best instrument, maximum temperature. In this case, the coefficient on the main variable of interest, maximum temperature, is highly significant. Indeed, the t-statistic is an extremely large 16.1969. Reassuringly, the effect is qualitatively correct: Lower temperature (and thus worse weather) deactivates voters.

One potential point of concern could be that the effect might appear somewhat small at just .0013654. What this means is that the natural logarithm of turnout is expected to increase by .0013654 for every one degree increase in maximum temperature. One way to gauge the size of this effect is to consider how much variation there usually is in maximum temperature. To measure the degree of variation we take all four maximum temperature observations for each county and subtract the smallest one from the largest one. Averaging over all counties, then, the average difference between the largest and smallest maximum temperature is 18.266 degrees. Thus, on average, over the four elections in question a county could expect to see a variation

	First Differencing	First Differencing, Just *MaxTemp*
MaxTemp	.0012907	.0013654
	(.0001021)	(.0000843)
MinTemp	-.0000689	-
	(.0001524)	
Precipitation	.0001832	-
	(.0000236)	
Snowfall	-.0008753	-
	(.0003074)	
Rained	-.0009136	-
	(.0019777)	
Snowed	-.0231807	-
	(.0056719)	
Change	.0371158	-.0144755
	(.0415164)	(.0414322)
$D\times$*Change*	-.1187854	-.0677074
	(.0459993)	(.0458258)
ln(*Income*)	.0814512	.1006257
	(.0215288)	(.021555)
$D\times$ln(*Income*)	.0156549	.0048232
	(.0070483)	(.0069654)
DemPres	.0714183	.0670259
	(.0067952)	(.0068342)
DemVP	.0325883	.0324666
	(.0051576)	(.0051572)
RepPres	.046874	.0471534
	(.0046156)	(.0045863)
RepVP	.0000747	-.0073871
	(.0043438)	(.0043049)
Year1988	.3128662	.2151129
	(.0702156)	(.0695822)
Year1992	.1617838	.0626655
	(.0706025)	(.07)
Year1996	-.0507852	-.0487923
	(.0039682)	(.0039691)

Table 3: Estimating ln(*Turnout*) with Weather Variables

in ln(*Turnout*) equal to $.0013654 \times 18.266 = .02494$. Thus, over the four years in the sample, turnout could be expected to vary about two and a half percent, simply from maximum temperature. While this may not seem overly large, we must remember that many elections are decided by close margins and that a two and a half percent increase in voter turnout is far from insignificant.

The regression that considers all six weather variables gives results that are somewhat more problematic. Before considering the problems, however, we first consider some of the positives. First of all, by a wide margin, the most significant weather variable is maximum temperature. This result gives us empirical reason to conclude that maximum temperature is the best instrumental variable, in addition to theoretical reasons. Furthermore, the effect of maximum temperature is very similar in both regressions, so this gives us reason to be more confident that our estimates are, indeed, correct.

However, the second most significant variable, precipitation, poses significant concern. In particular, the effect has the wrong sign–this analysis shows that voter turnout increases with more precipitation. Even worse, this effect is highly significant, with a t-statistic of 7.76271. At this time, we have no explanation for this effect. On the other hand, we should still note that the high significance of this effect is driven primarily by a small standard error, rather than a large effect. For example, precipitation of one inch would be very extreme. Indeed, it would place that county in the ninety-ninth percentile the sample. Even with such a high value for precipitation however, the effect would only be .018, which is less than the average effect of temperature at .024. At the ninetieth percentile, precipitation is thirty six hundredths of an inch. With this value, the effect falls to .00648, which is rather small.

The next most significant weather variables are the dummy variable indicating whether or not it snowed and the scalar variable indicating the snowfall in hundredths of inches. Both variables have rather large and significant effects. Furthermore, when combined with the precipitation variable, they more than outweigh the problematic estimator's small coefficient. Thus we conclude that it is only for rainfall that the estimators given are theoretically inconsistent.

Finally, the effects of minimum temperature and the dummy variable indicating whether or not it rained are statistically insignificant.

5.3.2 Predicting Partisan Performance with Weather Variables

Before developing an instrumental variables estimate of the effect of voter turnout on partisan results, it is prudent to examine the results of simply regressing the Democratic performance on weather variables. As with all the forthcoming analyses, we consider the first differencing estimator of the effect using just maximum temperature, as well as using all six weather variables. The results are given in Table 4.

We consider the regression which only contains maximum temperature first. Here the effect of temperature on Democratic performance is quite strong, with a t-statistic of 12.6587. The effect is positive, so a one degree increase in temperature increases Democratic performance by .0004228. This effect is quite large when we consider the mean swing between the largest and smallest maximum temperature, 18.degrees. Such a swing induces a .0004228×18.226*100=.77 percentage point increase in the performance of the Democratic candidate. This effect is far from trivial. Indeed, elections are often decided by smaller margins. This result is a new one establishing the partisan value of weather, contrary to the results of Knack (1994).

When all six variables are used, the analysis is somewhat more complicated. First, we are again reassured that maximum temperature remains the most significant predictor. Furthermore the estimate of the effect is not meaningfully different.

The next most significant effect is, as before, precipitation. Here the sign on precipitation is negative, so more rain means that Democrats do worse. Thus this effect agrees with the effect of maximum temperature: Better weather means better

	First Differencing	First Differencing, Just *MaxTemp*
MaxTemp	.000371	.0004228
	(.0000405)	(.0000334)
MinTemp	-.0001472	-
	(.0000605)	
Precipitation	-.0000543	-
	(9.37e-06)	
Snowfall	.0001168	-
	(.0001221)	
Rained	-.0029694	-
	(.0007855)	
Snowed	-.0037262	-
	(.0022529)	
Change	-.0261981	-.0113311
	(.0164904)	(.016437)
$D\times$*Change*	.0382472	.022443
	(.018271)	(.01818)
ln(*Income*)	-.0537696	-.0618195
	(.0085513)	(.0085513)
$D\times$ln(*Income*)	.0386146	.0438902
	(.0027996)	(.0027633)
DemPres	.0350546	.0354555
	(.0026991)	(.0027113)
DemVP	.0299537	.0297932
	(.0020486)	(.002046)
RepPres	-.0177456	-.0166307
	(.0018333)	(.0018195)
RepVP	.0104328	.0132953
	(.0017254)	(.0017078)
Year1988	.314656	.3637664
	(.0278898)	(.0276046)
Year1992	.4046064	.4528019
	(.0280434)	(.0277704)
Year1996	.0355477	.0353061
	(.0015762)	(.0015746)

Table 4: Estimating Democratic Vote Share with Weather Variables

performance for Democrats. Furthermore, the dummy variable for whether or not there was inclement weather is also negative, so the effect is further buttressed.

Though the strong performance of rainfall as a predictor of Republican success gels well with the effects of temperature at first glance, upon further analysis, this relationship is somewhat odd. Warmer temperatures were correctly measured as increasing turnout. Precipitation, on the other hand was, shown to be correlated with higher turnout as well. Thus the fact that the two predictors would agree that worse weather means better Republican performance is somewhat surprising. Also surprising is the strong significance of the rainfall dummy variable, which was not even significant. The measurement of rain harming Democrats is a direct refutation of the results of Knack (1994).

It is also surprising that minimum temperature has a statistically significant effect, since it too was insignificant to turnout. Increasing minimum temperature benefits Republicans, so this effect may seem odd. However, the effect is much smaller than the effect of maximum temperature, so this effect simply attenuates that one. In particular the negative sign on minimum temperature couple with the larger, positive sign on maximum temperature most likely signifies the presence of two effects. First, Democrats do better when the weather is better. Second, this effect is minimized when the weather is more variable. Such a minimization seems perfectly reasonable.

In the same vein as temperature and precipitation, the snow dummy variable shows that Democrats do worse when it snows. Finally, the scalar measure of snowfall shows an insignificant effect. As effects such as these have already been parsed, we proceed without discussion.

5.3.3 The Instrumental Variables Assumptions

Before giving the instrumental variables estimates of the effects of voter turnout on partisan results, we must first justify the use of the instrumental variables methodology. In particular, we must argue that the six assumptions required for the estimator to be unbiased do indeed hold. We consider them each in turn using the framework of Wooldridge (2003).

Assumption 1: Linear in Parameters The assumption that the true model is linear in all parameters is fundamental to most empirical analyses. We have no theoretical reason to think this condition will hold. However, the estimates are not meaningfully different if higher order terms are included. Thus we conclude that the model is well-enough approximated by the linear parameters.

Assumption 2: Random Sampling The random sampling assumption makes little sense in this context. Indeed, we have the entire population. One way people usually justify the use of standard regression models when the sample is the whole population is to posit that the observed population is actually a random sample from all potential universes. This assumption however, seems rather silly, and we are best served as methodologists simply noting the fact that we have the whole population, and proceeding with the rest of the analysis. To do anything else seems puerile. We should, however, note that in this case the idea of standard errors is also logically inconsistent. However, as using standard errors to measure the significance of results is standard in the literature–regardless of whether doing so makes logical sense–we report these numbers in this paper and discuss their potential meaning.

Assumption 3: Exogenous Instrumental Variables This assumption requires that all instrumental variables are exogenous to the model. The instruments are the weather variables, the economic variables, candidate home states, and years. The years are clearly exogenous. It is hard to imagine that weather could be affecting partisan results through any mechanism other than through voter turnout. By a very liberal definition the economic variables and candidate home states could be endogenous. However, candidates are chosen for many reasons, and the bias given by including the home states in the model cannot be great. As for the economic variables, the strength of the business cycle is much more powerful than anything the president could do. As a result, it seems hard to believe that it could truly be an endogenous variable. Furthermore, it is hard to imaging that presidents would be strategically causing the economy to do poorly for political gain, so we again, consider this effect to be minimal. Thus, we conclude this assumption holds.

Assumption 4: Rank Condition This is a technical assumption requiring that there are no perfect linear relationships between explanatory variables and that there is a meaningful exclusion restriction. Both of these assumptions clearly hold.

Assumption 5: Homoskedasticity This assumption requires that the conditional expectation of the variance of the errors is constant. We make this assumption for theoretical reasons. In particular, there is no reason to assume that the variance of the errors will be dependent on the weather, economic variables, candidate home states, or temporal variables.

Assumption 6: No Serial Correlation The final assumption is that there is no serial correlation of the errors. In other words, an error in one year does not affect the error in the next year. Because we use the first differencing estimator, we consider this to be a valid assumption. In particular, the first differencing estimator allows shocks to propagate through the time series. The only assumption required, then, is that a permanent shock in one election should not be correlated with a permanent chock in the next. This seems to be a very reasonable assumption.

5.3.4 The Instrumental Variables Estimates

We are now finally equipped to report the instrumental variables estimates of the partisan effects of voter turnout. In Table 5, we give the results of two instrumental variables regressions, one using maximum temperature as the instrument, the other using all six weather variables. We proceed by analyzing the results reported.

For consistency with our previous analyses, we begin by considering the results when the only instrument is maximum temperature. In this case, the effect of voter turnout on partisan results is quite significant with a t-statistic of 9.85235. The effect can be most easily stated as follows: for every one percent increase in voter turnout, we expect a .3 percentage point increase in how well the Democratic Party will have fared. Here we should note the confusing use of percentages. When we speak of percentage increases in voter turnout, we are actually referring to percents of percents, since turnout is, itself, a percent. So an example of a one percent increase in turnout is a move from 50% turnout to 50.5% turnout. This is the proper interpretation because the endogenous explanatory variable is $\ln(Turnout)$. On the other hand, when we speak of percentage point increases in Democratic performance, we are simply referring to movements in the percent. For example, a move from 50% to 51% is a one percent move.

From Equation 23, we can derive an additional interpretation of the regression results given. In particular, in a given county, we can assume that a marginal voter will be 30.96603% more likely to be a Democratic voter than the average partisanship of that district would indicate. In other words, in a county that is 40% Democratic, we would expect marginal voters to be 70.96603% Democratic. This interpretation, shows that the above estimate will be impossible for counties that are more than 70% Democratic. Only 48 out of 2,987 counties fit this description. Population wise, such counties tend to be large, but they still only make up five percent of the sample.

Regardless of the interpretation of the coefficient, instrumenting voter turnout

	First Differencing	First Differencing, Just *MaxTemp*
ln(*Turnout*)	.1302039	.3096603
	(.0209349)	(.0314301)
Change	-.0297651	-.0068486
	(.0174288)	(.0211824)
$D\times$*Change*	.0535849	.0434093
	(.0190895)	(.0230776)
ln(*Income*)	-.0750186	-.0929793
	(.0093286)	(.0114195)
$D\times$ln(*Income*)	.0432281	.0423966
	(.002939)	(.0035504)
DemPres	.0288688	.0147002
	(.0033079)	(.0042581)
DemVP	.0274793	.0197396
	(.0023385)	(.0029366)
RepPres	-.0245883	-.0312322
	(.0020669)	(.0025901)
RepVP	.0142447	.0155828
	(.0018222)	(.0022049)
Year1988	.3370113	.2971545
	(.0297098)	(.0361177)
Year1992	.4460196	.4333969
	(.0295565)	(.0357179)
Year1996	.0420046	.0504151
	(.0019396)	(.0025005)

Table 5: Predicting Democratic Vote Share with Instrumented ln(*Turnout*)

with maximum temperature gives an effect of voter turnout that very much favors the Democratic Party.

Though the results are somewhat muted, the analysis of the regression which includes all weather variables as instruments will be very similar. With all instruments, the effect of voter turnout is still highly significant, with a t-statistic of 6.2197. In particular we can expect a .13 percentage point increase for every one percent increase in voter turnout.

Alternatively, we can expect that the marginal voters in a given county will be thirteen percent more Democratic than the average voters in that county. Under this interpretation we can see that the estimates fails in counties that are more than 87% Democratic. Of all 2,987 counties, only one county fits this description. It holds one fifth of a percent of the nation's voting population.

The two methods presented above do indeed present vastly different effects of voter turnout on partisan results. However, the qualitative results are similar, as both regressions show that voter turnout has a significantly positive–and unignorable–effect on Democratic performance. Though the exact amount may be up for dispute, it is practically irrefutable at this point that voter turnout helps Democrats. This finding represents a new empirical result confirming the conventional wisdom.

5.3.5 Does Using ln($DemPer$) Make a Difference?

We now consider if using the natural logarithm of Democratic performance as the dependent variable makes any difference. We report the results of regressing the natural logarithm of Democratic performance on instrumented turnout in Table 6. We proceed by analyzing the results.

As always, we first consider the case in which turnout is only instrumented by maximum temperature. In this case, the effect is highly significant, with a t-statistic of 10.2849. The effect is interpreted as follows: given a 1 percent increase in voter

	First Differencing	First Differencing, Just *MaxTemp*
ln(*Turnout*)	.3575979	.740634
	(.0477071)	(.0720115)
Change	-.0287887	.0201249
	(.0397174)	(.0485325)
$D\times$*Change*	.1211157	.0993967
	(.0435018)	(.0528745)
ln(*Income*)	-.1879184	-.2262542
	(.0212582)	(.026164)
$D\times$ln(*Income*)	.0878084	.0860337
	(.0066976)	(.0081345)
DemPres	.0612041	.0309624
	(.0075382)	(.0097561)
DemVP	.0539026	.0373829
	(.005329)	(.0067283)
RepPres	-.068724	-.0829049
	(.0047102)	(.0059343)
RepVP	.0126426	.0154985
	(.0041524)	(.0050519)
Year1988	.6619745	.576903
	(.0677038)	(.0827517)
Year1992	.9088611	.8819189
	(.0673544)	(.0818356)
Year1996	.0927138	.1106655
	(.00442)	(.005729)

Table 6: Predicting ln(*DemPer*) with Instrumented ln(*Turnout*)

turnout, Democratic performance increases by .74%. Alternatively, the interpretation given by Equation 27 says that marginal voters are 74% more likely to be Democrats than average voters.

So how does this effect compare with that measured when using Democratic performance as the dependent variable? Qualitatively, the effects are no different, as increasing turnout helps Democrats. However, at many levels of baseline partisanship, the effect is quantitatively different. In particular, this effect is stronger than the one measured in the previous section when the baseline Democratic partisanship of the county is greater than 41.81%. This condition holds true for 1,933 of the 2,987 counties and eighty percent of the population. Thus, by almost all measures, one would consider this effect be even larger than that measured effect when the dependent variable is just Democratic performance, rather than its natural logarithm.

Unfortunately, because the measured effect is so large, it can only be true when Democratic performance is less than 57.45%. This condition holds true for 395 counties and 27.85% of the population. Thus, using this measure, far more of the sample produces an impossible estimate.

As before, when we consider the case in which turnout is instrumented by all six weather variables, the results are qualitatively similar. In particular, voter turnout helps Democrats very significantly, with a t-statistic of 7.49553. The effect shows that increasing turnout by one percent increases Democratic performance by .3575979 percent. Alternatively, marginal voters are roughly 36% more likely to be Democrats than average voters.

In this case, this estimator gives a larger effect for all counties with Democratic support above 36.41%. This condition holds in fully 2,451 out of 2,987 counties, accounting for 92.3% of the total population. Thus, as before, we conclude that the measured effect here is larger than in the case where $DemPer$ rather than $\ln(DemPer)$ is used as the dependent variable.

In this case, the effect can only possibly be true when baseline Democratic performance is less than .73.6595%. This condition excludes twenty-six counties and three percent of the population.

We conclude that it is better to use Democratic performance as the dependent variable rather than its natural logarithm. As such we do not consider the natural logarithm of performance as a dependent variable again. We make this choice for three reasons. First of all, the effects are qualitatively equivalent, so little is lost by not considering this dependent variable. Second, the effects are measured as larger when the logarithm used; so by not considering this method, we are only biasing the results against ourselves. Finally, using the logarithm greatly curtails the range over which the estimates are viable. As such we consider this dependent variable to be inferior.

5.4 Does the Effect Change with Baseline Partisanship?

Many theorists posit that the partisan effects of voter turnout stem from partisan defection (DeNardo, 1980; Grofman, Owen, and Collet, 1999). Under this argument, turnout will usually help the minority party. Furthermore, as counties become more extreme, the effect should be more extreme. This explanation, of course, is endogenous to the model, so if the instrumental variables are working properly, this effect will not show up if we look for it in the data using instrumented turnout. However, there are, nonetheless, reasons to think that the effect could systematically differ across baseline levels of partisanship.

To test this hypothesis, we apply the methods of section 5.3.4. Namely, we use first differencing to estimate the effect of the natural logarithm of instrumented voter turnout on Democratic performance. In order to test whether the effect changes with partisanship of the county, we break the sample into fifteen sub-samples. In particular, for each county we average the Democratic performance over the four elections in the data set. Next, we round this number to the nearest five percent.

Armed with the fifteen subgroups, we then re-perform all regressions for each subsample. Doing so allows the coefficients on all covariates to change with partisanship. We report the results of conducting this analysis using maximum temperature as the only instrument in Table 7.

Just using maximum temperature as an instrument, we obtain insignificant results for several subgroups; in particular the 15%, 75%, 80%, and 85% Democratic counties all have standard errors greater than their measured effects. The reason for this insignificance is simple: the sample size in these counties is just too small for any reasonable estimates to be made. Additionally, the estimate for the 65% Democratic county is also insignificant. However, as we see in the next paragraph, we disregard this county for other reasons.

The estimates for the 60%, 65%, and 70% Democratic counties are highly problematic. In particular, they give impossibly high effects, as marginal voters in those counties are estimated to vote Democratically more than one hundred percent of the time. Including these counties in our analysis would, in addition to being imprudent, also make effects appear that are not present. In particular, if one tried to diagnose a trend from the data, one might think that the effect is increasing because of the particularly large effects in these counties. Alternatively, one might think the effect is large at both ends of the spectrum because of a large effect measured for the 20% Democratic counties.

After eliminating the insignificant and impossible effects, two features of the changing effect jump out. First, the effect for the 20% Democratic counties is significantly larger than for the other counties. Second, the other counties all have roughly similar effects with no discernible trend in either direction. The average effect among these counties is roughly .18. This value is within less than one standard deviation of the measured effect for the 20% Democratic county. Thus we conclude that there

	First Differencing, Using *MaxTemp* as the Only Instrument
All Counties	.3096603
	(.0314301)
15% Democratic Support	-21.88551
	(668.9406)
20% Democratic Support	.362001
	(.2152006)
25% Democratic Support	.2238439
	(.0670603)
30% Democratic Support	.1981429
	(.0536434)
35% Democratic Support	.1173925
	(.0641848)
40% Democratic Support	.1267091
	(.0302113)
45% Democratic Support	.22055
	(.1277535)
50% Democratic Support	.1421449
	(.0662583)
55% Democratic Support	.2505091
	(.0840614)
60% Democratic Support	.6977256
	(.1761673)
65% Democratic Support	.4342933
	(.4492698)
70% Democratic Support	.5647619
	(.293786)
75% Democratic Support	2.844209
	(47.37117)
80% Democratic Support	.0175536
	(.0907644)
85% Democratic Support	.1103622
	(.7501718)

Table 7: Comparing the Effect Across Different Levels of Baseline Democratic Support When Using Maximum Temperature as the Instrument for ln(*Turnout*)

is no change in the effect by partisanship.

One point of interest that comes out of this analysis is the potential to explain the rather large measured effect for all counties, which is more than twice the measured effect when using all instruments. In particular, in almost all subgroups the measured effect is much lower than .3096603, with the notable exception of the subgroups we threw out because their measured effects were impossible. Thus, we might be led to conclude that it is these counties that are biasing the measured effect upwards.

Regardless, when using maximum temperature as the only instrument, it does not matter if the sample is broken into subgroups by partisanship: The qualitative effects remain the same.

The analysis is very similar if we use all instruments to predict turnout. The results of first differencing estimates of the effects of fully instrumented turnout are given in Table 8.

As in the case when there is only one instrument, the effects of fully instrumented voter turnout are statistically insignificant at the tails. In particular, in the 15%, 20%, 75%, 80%, and 85% Democratic counties, the t-statistics are too small to give statistically significant effects. As before, the reason for the insignificance is the lack of sample size at the tails. The estimates of the effect in 45% and 65% Democratic districts are also insignificant. However, the measured effects are consistent with those in neighboring sub-samples, so we conclude that the insignificance is driven by large standard errors. This is a particularly peculiar condition for the 45% Democratic sub-sample as this is one of the very largest sub-samples. We have no explanation for what might be inflating these standard errors.

Unlike the estimates given when the only instrument is maximum temperature, the estimates given when all six instruments are used do not give any logically impossible estimates. This is a strong argument in favor of using all six instruments.

With the exception of a strong peak in the 55% and 60% Democratic counties

	First Differencing, Using All Instruments
All Counties	.1302039
	(.0209349)
15% Democratic Support	.1381497
	(.1772244)
20% Democratic Support	-.036956
	(.0327359)
25% Democratic Support	.1952997
	(.0490379)
30% Democratic Support	.1865837
	(.0435322)
35% Democratic Support	.1767459
	(.0589091)
40% Democratic Support	.0689882
	(.0243778)
45% Democratic Support	.086391
	(.0820438)
50% Democratic Support	.1525425
	(.0573393)
55% Democratic Support	.2951664
	(.0689787)
60% Democratic Support	.3340597
	(.0813396)
65% Democratic Support	.1720517
	(.1230934)
70% Democratic Support	.1666086
	(.0956358)
75% Democratic Support	-.1975494
	(.3190405)
80% Democratic Support	.0614755
	(.0686241)
85% Democratic Support	-.053008
	(.0398415)

Table 8: Comparing the Effect Across Different Levels of Baseline Democratic Support When Using Fully Instrumented $\ln(Turnout)$

and a trough at the 40% and 45% Democratic counties, the measured effect is very consistent across in all of the counties in which there is a large enough sample to measure significant effects. The existence of the peaks and troughs in the effect might lead us to conclude that the effect is increasing with Democratic partisanship. In other words, higher voter turnout is always good for Democrats, and more so when counties are more extreme. However, because this effect is not continuous, we are reluctant to make this conclusion.

This test also gives us another reason to prefer using all instruments: Unlike the case in which we only used one instrument and the overall measured effect seemed to be driven by extreme counties, when all instruments are used, the effects are roughly constant, regardless of whether the sample is completely aggregated or broken into subgroups. In other words, the 13% effect measured when all counties are used fits right in the middle of the range of estimates when the sample is separated into groups based upon partisanship.

5.5 Does the Effect Change over Time?

We now turn to our final set of statistical analyses to answer the question of whether the partisan effect of voter turnout is changing over time. To address this question we maintain the same methodology we have been working with: first differencing with instrumental variables. The change we make in this section is that for each instrumentation strategy we estimate three effects. One is based on first differencing between 1988 and 1992, one is for 1992 to 1996, and the final one is for 1996 to 2000. We report the results of conducting these three regressions with maximum temperature as the only instrument in Table 9.

When temperature is the only instrument, the effect is changing quantitatively, but not qualitatively over time. In particular, in all time periods, the effect is positive, so Democrats benefit from higher voter turnout. In addition, the effect does not appear

	All Years	1988-1992	1992-1996	1996-2000
ln(*Turnout*)	.3096603	.8126211	.1123316	.2451023
	(.0314301)	(.2162557)	(.0389017)	(.0392277)
Change	-.0068486	.3317155	.1000537	-.0965472
	(.0211824)	(.1206508)	(.0340694)	(.0168637)
$D\times$*Change*	.0434093	-	-.2556294	-
	(.0230776)		(.0408424)	
ln(*Income*)	-.0929793	-.5341369	-.0103603	.0924767
	(.0114195)	(.0998509)	(.0197315)	(.0146337)
$D\times$ln(*Income*)	.0423966	-	.031364	-
	(.0035504)		(.0030875)	
DemPres	.0147002	-.0356271	-	.0404083
	(.0042581)	(.0199098)		(.00641)
DemVP	.0197396	.00031	-	.0253718
	(.0029366)	(.0102345)		(.0056573)
RepPres	-.0312322	-	-.0100026	-.0361454
	(.0025901)		(.004562)	(.003109)
RepVP	.0155828	-	.0412802	-.0255144
	(.0022049)		(.0031824)	(.0034282)
Year1988	.2971545	-.2907764	-	-
	(.0361177)	(.0484254)		
Year1992	.4333969	-	.2815218	-
	(.0357179)		(.0307885)	
Year1996	.0504151	-	-	.0733178
	(.0025005)			(.003645)

Table 9: How is the Effect Changing over Time? Using Maximum Temperature as the Only Instrument for ln(*Turnout*)

to be trending upward or downward in a meaningful way: The lowest effect measured is for 1992-1996.

However, the effect measured for the time frame of 1988-1992 is highly problematic. In short, it is simply too large. The measured effect could only hold in counties with less than 20% Democratic support. Such counties are extremely rare: There are only fifteen of them and they contain one twentieth of one percent of the nation's population. One potential explanation for the overly large effect is the large growth of the third-party movement from 1988 to 1992. However, given the fact that voter turnout is instrumented by weather, it is hard to see how this mechanism could work.

Problems with the first pairing of elections aside, these results further bolster our analysis that higher voter turnout increases Democratic performance.

As we can see in Table 10, the effect measured over time when all instruments are used is very similar to the case in which only the best instrument is used. In particular, the effect is at a maximum in 1988-1992 and at a minimum in 1992-1996.

The minimum effect given, however, is qualitatively very different from effects measured elsewhere. Indeed, this method says that in 1992-1996, higher voter turnout hurt Democrats. To make matters worse for producing a consistent analysis, the effect is highly significant in the wrong direction, with a t-statistic of -8.03563. The only explanation we can offer is that the candidacy of Ross Perot is somehow complicating matters. However, as before, we have no intuition as to what the causal mechanism could be, because turnout is instrumented.

The maximum effect is also problematic. In particular, it can only possibly hold true in 257 counties containing 2.5% of the population.

Regardless of major problems in both the best measured effect and worst measured effect for Democrats, the numbers do not show any trend over time. Thus, we conclude that the effect is simply fluctuating over time. In other words, it might not be a hard and fast rule that turnout always helps Democrats. But it does do so in most

	All Years	1988-1992	1992-1996	1996-2000
ln(*Turnout*)	.1302039	.6890993	-.2271204	.1398575
	(.0209349)	(.1074425)	(.0282646)	(.03227)
Change	-.0297651	.2681903	.2326271	-.097882
	(.0174288)	(.0685827)	(.0331254)	(.0153173)
$D\times Change$	.0535849	-	-.2416086	-
	(.0190895)		(.0418145)	
ln(*Income*)	-.0750186	-.4804694	-.0340317	.0962599
	(.0093286)	(.0551431)	(.0201138)	(.0132817)
$D\times\ln(Income)$	.0432281	-	.0357656	-
	(.002939)		(.0031412)	
DemPres	.0288688	-.0252052	-	.0478667
	(.0033079)	(.0114049)		(.0057234)
DemVP	.0274793	.0053193	-	.0305771
	(.0023385)	(.0063233)		(.0050843)
RepPres	-.0245883	-	.0219494	-.0385234
	(.0020669)		(.0038529)	(.0028034)
RepVP	.0142447	-	.0236965	-.0211144
	(.0018222)		(.0029168)	(.0030493)
Year1988	.3370113	-.2633973	-	-
	(.0297098)	(.0245537)		
Year1992	.4460196	-	.3386646	-
	(.0295565)		(.0311771)	
Year1996	.0420046	-	-	.0664577
	(.0019396)			(.0031611)

Table 10: How is the Effect Changing over Time? Using Fully Instrumented ln(*Turnout*)

circumstances.

6 Implications

In the previous section, we offered strong evidence that there is a partisan effect of voter turnout. The effect is large and pro-Democratic, and, for the most part, unchanging over time and baseline county-level partisanship. We now turn to examining the consequences of these findings. First, we consider the theoretical implications. Second, we briefly consider the practical implications of our findings.

6.1 Theoretical Implications

We consider the theoretical consequences of our findings in three frameworks. First, we remain in the framework developed in section 3 and determine that our results show that the conditional probability of marginal voters' being Democrats is higher than for other voters. Second, we consider our results in the framework of the two effects model. In particular, we argue that because the effect is so consistently in favor of the Democrats, this model holds little weight. Finally, we consider the three questions posed by Grofman, Owen, and Collet (1999) and answer all three in turn.

6.1.1 The Model Guiding this Paper

Before proceeding to analyze the results of this paper with respect to the literature, it is worthwhile to fix our ideas about the measured effect of voter turnout in the framework developed earlier in this paper. In particular, measuring a positive impact of voter turnout means that marginal voters in most counties tend to be more Democratic than average voters in those counties. To put that another way, the covariance of voters' tendency to vote and tendency to vote Democratic is negative. So, all else equal, learning that a voter is more likely to vote on Election Day will make us more likely to think that he or she will vote for the Republican Party.

The driving force, then, behind the strong measured partisan impact of voter turnout, is simply the disproportionate strength of the Democratic Party among marginal voters.

6.1.2 The Two Effects Model

The results presented in this paper suggest that the composition effect is stronger than the defections effect. In particular, the composition effect is confirmed because it is simply a binary version of the model discussed above. In particular, the composition effect rests on there being two types of voters: core and peripheral. In this effect, higher turnout helps the party with more peripheral voters. The results presented in this paper, then, show that this effect holds, and that, indeed, it is the Democratic Party whom it helps.

The defection effect, on the other hand, is debunked. In particular, the fact that the effect does not meaningfully change with baseline partisanship is evidence of this fact. However, by all accounts, the defection effect described by DeNardo (1980) is an endogenous effect, so it is no surprise that using instrumented turnout eliminates the effect. However, if the effect is endogenous, it is not clear that we should be conflating it with the exogenous effects.

6.1.3 The Three Questions

We conduct the bulk of our theoretical analysis in the framework of the three questions posed by Grofman, Owen, and Collet (1999). We consider them each in turn.

Are low turnout voters more likely to vote Democratic than high turnout voters? Grofman, Owen, and Collet (1999) posit that the answer to this question is yes. This study confirms this hypothesis with very strong evidence. In particular, because the analysis rests on using an instrumental variable representing the cost of voting, it precisely picks out low turnout voters. Indeed, one of the main theoretical interpretations of our results is that marginal voters are more likely to vote for the Democratic Party than regular voters. Assuming the relationship is monotonic, then, we can safely say that low turnout voters are more likely to vote Democratic than high turnout voters.

If we do not assume monotonicity, then we cannot make so broad a statement as the question requires. However, if the relationship is not monotonic the question does not make particular sense. Indeed, in the absence of monotonicity, the reasonable question to ask is if marginal voters are different than average voters.

Should we expect that elections in which turnout is higher are ones in which we can expect Democrats to have done better? Grofman, Owen, and Collet (1999) argue that the answer to this question is no. In this paper, we offer evidence that the contrary is true: all else equal, we can expect that Democrats will have done better in elections with higher turnout. At first glance, it might appear that we have already answered this question, as our estimated coefficient on the effect of voter turnout is positive. However, this does not mean that Democrats will always hope for higher turnout. In particular, Democrats will never hope for higher turnout in very Republican counties. Though their performance percentage-wise might be positively affected, there will still be more Republicans voting, which is a negative effect for Democrats.

Before answering this question, then, we must define what it means for Democrats to do better in a county. There is a very natural definition. In particular, we say that a change in turnout is good for Democrats if it positively changes the spread of votes, where we define the spread as the difference between total Democratic votes and total Republican votes. In order to determine the change of spread we apply the following methodology: First, we obtain from Tables 7 and 8 the turnout effect at each level of county-wide Democratic support. From Equation 23 and the information in these tables, we know the probability that marginal voters will be Democrats. Thus, we can define the expected change in the spread per new voter as:

$$\Delta S = \Pr(d_i) - \Pr(r_i), \tag{29}$$

where $\Pr(d_i)$ is the probability a marginal voter in county i will vote Democrat, and $\Pr(r_i)$ is the probability the voter will vote Republican. Of course, we know these probabilities, so we have:

$$\Delta S = 2\frac{D_i}{T_i} + 2\beta_i - 1, \tag{30}$$

where $\frac{D_i}{T_i}$ is the Democratic partisanship and β_i is the measured effect of voter turnout. We report this spread change per additional voter in Table 11, using the estimates garnered from using all instruments, as well as just maximum temperature.

Regardless of which method we use, the effect of increased voter turnout is always positive for Democrats in counties with Democratic support above the 45% level. This condition holds in 1,856 out of 2,987 counties. Furthermore, these counties contain 78.3% of the total population. Even in counties with lower Democratic support, the negative effects for Democrats is nowhere near large enough to outweigh the positive effects for Democrats at the other end of the spectrum. Thus, we conclude that we can expect that, all else equal, Democrats will do better when there is higher turnout.

Of course, the phrase “all else equal” cannot be understated in this context. Turnout is an endogenous variable, and we have not counted those effects, so it is entirely probable that there could be many elections in which higher turnout was somehow correlated with better Republican performance. However, as a Bayesian, one would have to completely disregard the analyses in this paper in order not to update one’s prior on the partisan outcome of an election in a manner beneficial to

	ΔS, All IVs	ΔS, *MaxTemp*
15% Democratic Support	-.4237006	-44.47102
	(.3544488)	(1337.8812)
20% Democratic Support	-.673912	.124002
	(.0654718)	(.4304012)
25% Democratic Support	-.1094006	-.0523122
	(.0980758)	(.1341206)
30% Democratic Support	-.0268326	-.0037142
	(.0870644)	(.1072868)
35% Democratic Support	.0534918	-.065215
	(.1178182)	(.1283696)
40% Democratic Support	-.0620236	.0534182
	(.0487556)	(.0604226)
45% Democratic Support	.072782	.3411
	(.1640876)	(.2555070)
50% Democratic Support	.305085	.2842898
	(.1146786)	(.1325166)
55% Democratic Support	.6903328	.6010182
	(.1379574)	(.1681228)
60% Democratic Support	.8681194	1.5954512
	(.1626792)	(.3523346)
65% Democratic Support	.6441034	1.1685866
	(.2461868)	(.8985396)
70% Democratic Support	.7332172	1.5295238
	(.1912716)	(.5875720)
75% Democratic Support	.1049012	6.188418
	(.6380810)	(94.7423400)
80% Democratic Support	.722951	.6351072
	(.1372482)	(.1815288)
85% Democratic Support	.593984	.9207244
	(.0796830)	(1.5003436)

Table 11: The Politically Relevant Effect: The Change in the Spread For Each New Voter

Democrats when presented with the sole fact that turnout was exceptionally large.

If turnout were to have increased in some given election, would Democrats have done better? Grofman, Owen, and Collet (1999) claim that this question is unanswerable. The data presented in this paper, however, provide a strong answer to this question–stronger even than the answers to the other two questions. The fundamental methodology employed in this paper the technique of instrumental variables. What this technique does is separate out the endogenous effects from the exogenous effects of an explanatory variable. In other words, the regressions presented in this paper tell us what happens when turnout increases because of better weather.

Unequivocally, this paper suggests that, if weather were to have been better in some given election, Democrats would have done better. The method of instrumental variables allows us to take this argument one step further. If we were to increase turnout by making the weather better, we could expect that Democrats would do better. Assuming that all exogenous shocks to turnout behave similarly, then, we can firmly answer this question that was hitherto deemed unanswerable: If turnout were to have increased in some given election, Democrats would probably have done better.

6.2 Practical Implications

The evidence presented in this paper has ramifications that reach far beyond theory. In particular, there is a wide array of practical implications, of which we consider two. In particular, we first consider how these findings should affect the behavior of political parties. We then consider what light these findings may shed upon our stances on voting reform.

6.2.1 Party Behavior

The prescriptions of this analysis for the behavior of political parties are rather clear. Democrats should act to increase voter turnout while Republicans should act to suppress turnout. To those ends, both parties have mechanisms they can employ.

While both parties are well-served by targeted get-out-the-vote efforts, the Democratic Party is well-served by general efforts to increase voter turnout. To that end, Democrats could support public service announcements and the like, as they would mobilize voters in a non-partisan–and thus pro-Democratic–manner. Furthermore, it is in the Democratic Party's best interest to lower barriers to voting. To that end, Democrats should work towards reforms such as same-day registration and voting holidays.

Republicans face a harder task, as it is hard to imagine a political party overtly opposed to voter turnout. Indeed, if the voters perceive such a stance, voters could very well hold it against the party that holds it. Of course, Republicans do have tools at their disposal to lower voter turnout. In particular, Ansolabehere and Iyengar (1995) have shown that negative advertising demobilizes voters. Thus, it is in the best interests of the Republic Party to get into a negative ad campaign war, as doing so depresses turnout at the Democrats' expense.

The above political suggestions may seem somewhat silly. For the most part, the parties already follow these strategies. We interpret this fact as all the more evidence that the results presented in this paper are accurate.

6.2.2 Voting Reform

This analysis also sheds light on some important questions regarding voting reform. In particular, if there were no partisan effect of voter turnout, then one could argue that it is unnecessary to conduct reforms that make it easier to vote. Doing so would change nothing in the political process and only cost the state money. The results in this paper show that this conclusion is wrong. Decreasing the barriers to vote would have a partisan effect.

The existence of a partisan effect, however, does not necessarily mean that barriers to voting should be decreased, however. From a normative perspective, the goal we are truly after is making the voter represent the electorate. Thus, if the partisan effect of increasing voter turnout increases the bias away from true representations, we might have reason to oppose reducing barriers to voting.

7 Conclusion

In this paper, we have shown that using instrumental variables provides an unbiased estimate of the partisan effects of voter turnout. In particular, using weather as an instrument, we have shown that increased turnout significantly benefits Democrats. This effect is consistent across counties of various levels of partisanship. Furthermore, it does not appear to be consistently changing over time.

These findings significantly illuminate the theory in regards to voter turnout. In particular, these results show that the primary exogenous mechanism through which turnout affects elections is the composition effect. In other words, when turnout is increased, newly mobilized voters are disproportionately Democratic.

Furthermore, these results illuminate a question that has been claimed to be unanswerable: If one could increase voter turnout, would it help Democrats? We find that the answer to this question is, resoundingly, yes.

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