Natural Disasters that Cause No Damage: Retrospective Voting and a Reanalysis of 'Make it Rain'

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December 16, 2019

Abstract

A large empirical literature examines how voters react to different types of information when considering an incumbent politician or political party. A number of recent studies use weather damage and the political response to the damage as a quasi-experiment to examine retrospective voting. We highlight two frequent shortcomings in this literature: the prevalence of missing weather damage information and spatial correlation in the political response. We reevaluate the evidence in Gasper and Reeves [2011], a seminal study. Contrary to Gasper and Reeves [2011] we find little evidence in favor of an attentive electorate. There are two key differences in our analysis. First, roughly half of the panel observations, including a third of the observations with a weather-related Presidential Disaster Declaration, have missing weather damage. We drop these observations from the analysis rather than assume zero damage. Second, we allow for the documented spatial correlation in the disaster response.

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1 Introduction

Models of voting behavior often assume that the electorate is retrospective (e.g. Key [1966]; Kramer [1971]; Torsten Persson and Tabellini [1997]). A large empirical literature examines how voters evaluate political performance and react to different types of information when considering an incumbent politician (Anderson [2007] and Healy and Malhotra [2013] provide reviews). Whether voters hold incumbent politicians responsible for random events outside of their control, or only for the political response to these events, is a key topic in the literature.

The early empirical literature on retrospective voting focuses on how the electorate responds to economic conditions when voting for incumbent politicians or political parties (e.g. Anderson [2007]). There are several shortcomings of using information about economic conditions to test theories of retrospective voting. These include the often tenuous link between political actions and economic performance, and the challenge that economic conditions are not randomly assigned (e.g. Alesina et al. [1993]; Carsey and Wright [1998]; Healy and Malhotra [2010]; Healy and Malhotra [2013]).

A number of recent studies use weather damage and the political response to the damage as a quasi-experiment to examine retrospective voting (e.g. Healy and Malhotra [2009]; Bechtel and Hainmueller [2011]; Gasper and Reeves [2011]; Cole et al. [2012]; Chen [2013]). Random weather damage allows for a clear causal interpretation for both the exogenous damage and the subsequent political actions on the reelection vote share.

Gasper and Reeves [2011], a seminal paper in this literature, are among the first to use the quasi-experiment to study retrospective voting.[1] A "responsive"

[1] Gasper and Reeves [2011] has been cited at least 260 times (Google Scholar, December, 2019), including by studies that examine the impact of natural disasters on political opinion and voting around the world in India (Cole et al. [2012]), Chile (Carlin et al. [2013]), Russia (Lazarev et al. [2014]), and Pakistan (Kosec and Mo [2017]). The results of the study feature in at least two prominent books (Kriner and Reeves [2015] (winner of the 2016 Richard E. Neustadt Award for the best book on the American Presidency), and Sylves [2019]), and have been widely covered in the popular media, including by CNN, FiveThirtyEight, Solon, and The Washington Post.

electorate will be less-likely to vote for incumbent politicians or political parties following a disaster due to the personal costs of the disaster damage. An "attentive" electorate will evaluate politicians based on their response to the disaster and, for example, be more likely to support politicians who help secure federal disaster assistance.[2]

Gasper and Reeves [2011] examine US gubernatorial and presidential elections and find evidence supportive of both types of voting behavior. Greater weather damage in the months before an election leads to larger reductions in the county vote share for incumbents. At the same time, vote shares are higher for governors who request federal disaster assistance and for presidents who grant the assistance via a Presidential Disaster Declaration. The authors conclude that, overall, the negative vote share impact of a natural disaster "is dwarfed by the response of attentive electorates to the actions of their officials" (p1).

In this paper we reevaluate the evidence on retrospective voting in Gasper and Reeves [2011]. We find little evidence in favor of an attentive electorate. Two factors most explain the difference in our results.

First, we show that the weather damage data suffer from significant measurement error. For example, there is missing (non-reported) weather damage for half of the observations in the panel used to estimate the presidential vote share model. Remarkably, this includes roughly a third of the counties with a weather-related Presidential Disaster Declaration. Gasper and Reeves [2011] impute these missing values as zeros. We only include observations in our main analysis that have reported weather information. In particular, we view it as incorrect to impute zero values for missing observations when there is a documented disaster in the county.

There are also a large number of counties with disaster declaration requests

[2] We follow the terminology of Gasper and Reeves [2011] in our analysis. Other studies emphasize a more nuanced view of retrospective voting. For example, Woon [2012] and Healy and Malhotra [2013] distinguish between two types of attentive voters: reward-punishment (electoral sanction) and electoral selection. Healy and Malhotra [2010] emphasize that it can be rational for voters to respond to weather damage by voting against incumbent politicians, for example, if voters are information-constrained and conclude that at least some portion of the disaster damage is the consequence of political decisions.

and zero reported weather damage. The weather damage information for these counties is almost certainly misreported. Why would a governor request, and frequently receive, disaster assistance if there is no disaster damage? Regardless, the quasi-experimental research design that seeks to evaluate whether the electorate can separate the proactive actions of politicians from the random weather damage, makes no sense if there is zero reported weather damage. Our preferred sample drops observations with a weather-related disaster request and zero reported weather damage.

Second, weather damage is spatially correlated. For example, when a hurricane hits a state, contiguous counties in the state are more likely to have similar weather damage than counties at opposite sides of the state. At the same time, there is also state-level spatial correlation in the decision to approve or deny a disaster request. Presidential Disaster Declaration requests are made on a state-by-state basis. The governor must submit the list of disaster-affected counties in the state to the President when requesting a Presidential Disaster Declaration. The state-level spatial correlation in the approval or denial of disaster assistance is made stronger in Gasper and Reeves [2011] due to a coding decision. The authors assign *all* counties in a state a denied disaster request if there is a denied request for *any* county in the state in the six months before an election.

Gasper and Reeves [2011] do not allow for spatial correlation in their econometric model. As a consequence, the standard errors for the estimated weather damage and disaster assistance coefficients are underestimated (e.g. Moulton [1986]; Angrist and Pischke [2008]; Cameron and Miller [2015]; Abadie et al. [2017]). This leads the authors to dramatically overstate the evidence in favor of an attentive electorate. None of the main results reported in Gasper and Reeves [2011] are statistically different from zero at conventional significant levels after accounting for spatial correlation.

Overall, we find that the presidential model results imply a responsive electorate. The negative effect of weather damage on a president's reelection vote share is six to eight times larger in our analysis than is reported in Gasper and Reeves [2011]. Imputing missing weather damage observations as zero biases the estimated coefficient towards zero. We can statistically reject that the estimated damage coefficients in our analysis are equal to those in Gasper and Reeves [2011]. Further, we estimate that the approval of disaster assistance has a smaller impact on reelection vote share than in Gasper and Reeves [2011]. The net effect is that the estimated presidential reelection vote share is lower (or indistinguishable from zero) in all counties with a Presidential Disaster Declaration in the six months prior to the election (hereafter "disaster counties") and non-missing damage information.

The gubernatorial model results are inconclusive. Governors who successfully request federal assistance receive an increase in their reelection vote share. In contrast to Gasper and Reeves [2011], we find no effect on the gubernatorial reelection vote share when a governor's request for assistance is denied. Voters only reward governors for their actions when a disaster request is approved, even though the decision to approve the request is mostly outside of the governor's control. As in the presidential model, the weather damage coefficient estimates are negative. However, we are unable to conclude whether the positive federal assistance vote share effect outweighs the negative damage effect in any of the disaster counties given the size of the confidence intervals. Accounting for the documented spatial correlation in disaster assistance results in large confidence intervals. This is true in both our replication of Gasper and Reeves [2011] and in our reanalysis that uses smaller samples.

Finally, our study highlights a serious measurement error concern in a frequently used weather damage database: the National Weather Service NCDC monthly Storm Data publications (and by extension SHELDUS).[3] These data have been used by researchers examining questions related to natural disasters in a number of fields, including political science (e.g. Healy and Malhotra [2009]; Healy and Malhotra [2010]; Gasper and Reeves [2011]), economics (e.g. Sheldon and Zhan [2019]), and finance (e.g. Cortes and Strahan [2017]). A critical feature of the National Weather Service data is that they are self-

[3] The Special Hazards Events and Losses Database for the United States (SHELDUS) use the National Weather Service NCDC monthly Storm Data publications as a main source of primary information.

reported by individual weather stations, and are thus susceptible to bias from unreported (i.e. "missing") data. Research that relies on this damage information should be viewed with circumspection.

The paper proceeds as follows. Section 2 describes the sample, variables, and econometric models in Gasper and Reeves [2011]. We highlight the poor quality of the weather data, and the importance of accounting for spatial correlation in the analysis. Section 3 focuses on the presidential vote share model. We replicate the results of Gasper and Reeves [2011], and reanalyze the model using a complete case analysis that allows for spatial correlation. Section 4 repeats the analysis for the gubernatorial vote share model. We summarize and discuss our results in Section 5.

2 Data and Econometric Model

Gasper and Reeves [2011] estimate a linear regression model using Equation 1 and a county-by-year panel dataset.

$$\begin{aligned} y_{ct} &= \beta_1 Damage_{ct} + \beta_2 Disaster_{ct} + \beta_3 Turndown_{ct} + \beta_4 PresVote(Lag)_{ct} \\ &\quad + \beta_5 PresVote(2Lag)_{ct} + \beta_5 Income_{ct} + \alpha_c + \gamma_t + \epsilon_{ct} \end{aligned} \tag{1}$$

y_{ct} is the dependent variable and measures the incumbent two-party (Democrat and Republican) vote share in county c in election year t. The model is run separately for gubernatorial elections from 1970-2006, and for presidential elections from 1972-2004.[4] The gubernatorial vote share model only includes election years when an incumbent governor is running for reelection. The presidential vote share model considers all presidential elections and does not distinguish between voting for an incumbent president and the incumbent president's political party.[5]

[4] Equation 1 is the presidential vote share model. The gubernatorial model is the same except that the twice lagged presidential vote share control variables are replaced with a once lagged gubernatorial vote share control variable.

[5] Special elections are excluded from the panel. Since elections are held in November, the year subscript t is the same for the dependent and independent variables in the model even though the disaster damage occurs before the election.

The attentive and responsive electorate hypotheses are captured by three coefficients in the model. β_1 estimates the correlation between vote share and disaster damage, after controlling for the political response and the other control variables. A positive coefficient estimate for β_1 is support for the responsive electorate hypothesis. $Damage_{ct}$ is defined as the natural log of the county-level weather damage for the six months prior to the election per 10,000 county residents. The weather damage information is from the Special Hazards Events and Losses Database for the United States (SHELDUS). We discuss the SHELDUS data in detail in the next subsection.

$Disaster_{ct}$ is an indicator variable for whether there is a Presidential Disaster Declaration in the county during the six months prior to the election. A Presidential Disaster Declaration provides federal assistance to repair public infrastructure, as well as, cash grants and subsidized loans directly to individual residents. A positive coefficient estimate for β_2 is support for the attentive electorate hypothesis. The source of the Presidential Disaster Declaration information is the Federal Emergency Management Agency (FEMA).

$Turndown_{ct}$ is an indicator variable equal to one if the disaster request is denied. A negative coefficient estimate for β_3 in the presidential vote share model and a positive coefficient in the gubernatorial model is support the attentive electorate hypothesis. One important limitation of the disaster denial information in Gasper and Reeves [2011] is that the exact counties considered in the denied requests are unknown. All of the counties in a state have the same value for $Turndown_{ct}$ if there is a denied Presidential Disaster Declaration request for the state in the six months prior to an election. The source of the $Turndown_{ct}$ information is the Public Entity Risk Institute.

The model includes several control variables. $Income_{ct}$ is the median household income as reported in the last decennial US Census prior to the disaster. $PresVote(Lag)_{ct}$ and $PresVote(2Lag)_{ct}$ are the lagged and twice lagged two-way vote share for the presidential candidate of the governor's party in the previous two presidential elections. α_c are county fixed effects and control for county-specific factors that are constant over the data panel (e.g. geography). γ_t are time fixed effects and control for common yearly factors that impact all counties (e.g. an economic recession).

The model assumes that the classical OLS assumptions regarding the distribution of the conditional variance of the error term are valid. No adjustments are made to account for spatial correlation.

2.1 Disaster Damage Data

The accuracy of the county weather damage information is critical to the quasi-experimental research design that seeks to separately test whether voters are (more) responsive or attentive. The causal question of interest is whether voters reward elected politicians for their actions (attentive electorate), or only punish politicians for the random state of the world (responsive electorate). That is, do victims of a natural disaster vote more frequently for presidents and governors who provide federal assistance? If the damage information is inaccurate, then estimating a retrospective voting model using Equation 1 will lead to biased conclusions, unless we make strong assumptions regarding non-reporting and measurement error. Moreover, there is no reason to expect that using inaccurate damage information will lead to "conservative" estimates that are biased towards zero (e.g. Loken and Gelman [2017]).

The weather damage data are from SHELDUS. SHELDUS compiles the weather data from several primary sources. The main source is the National Weather Service NCDC monthly Storm Data publications. SHELDUS aims to fill an empirical gap by providing monthly weather damage data for each US county across more than fifty years. We are not aware of another panel database that combines the detail and frequency of the weather damage data for the entire US. Due to this fact, SHELDUS (and the underlying Weather Service data) are frequently used by researchers in political science (e.g. Healy and Malhotra [2009]; Gasper and Reeves [2011]), economics: (e.g. Sheldon and Zhan [2019]), and finance (e.g. Cortes and Strahan [2017]), among other fields.

A critical feature of the National Weather Service data is that they are self-reported by individual weather stations. One consequence of the self-reporting is that the NCDC monthly Storm Data publications, and by extension SHEL-

DUS, are susceptible to bias from unreported (i.e. "missing") data.[6] In our reevaluation of Gasper and Reeves [2011] we show that the missing data problem is severe. There are 3,316 disaster counties in the presidential panel estimated by Gasper and Reeves [2011]. Gasper and Reeves [2011] impute missing observations as zeros in their analysis. A third of these disaster counties in Gasper and Reeves [2011] have zero reported monthly damage during the six months that include the disaster.

2.2 Disaster Declaration Spatial Correlation

There is spatial correlation in the level of disaster damage. Hurricanes, floods, and other natural disasters can cause tremendous weather damage to personal property and public infrastructure in counties impacted by the disaster. The correlation in weather damage is greater between counties affected by the same natural disaster, than it is between a disaster-affected county and a non-affected county.

There is also spatial correlation in the decision to approve or deny a Presidential Disaster Declaration request. The first step in the Presidential Disaster Declaration process is for the governor of a state to submit a written letter of request to FEMA. The letter must contain the list of proposed disaster counties in the state and supporting documentation, including preliminary damage cost estimates, that justifies the need for federal assistance. FEMA then makes an official recommendation to the US president. The president ultimately decides whether or not to grant the request for disaster assistance.

Presidential Disaster Declaration requests are approved state by state. If a natural disaster impacts multiple US states, the governor of each impacted state must submit a separate request. It is frequently the case that all of the proposed counties in the governor's request will be approved or denied federal assistance. Further, due to data limitations and a coding decision in Gasper

[6] Gallagher [2013] examines all flood-related Presidential Disaster Declarations from 1960-2007 and finds that only 8.5% appear in SHELDUS (2008). Conversations with researchers who compiled SHELDUS (2008) confirm that cost information on the majority of the flooding Presidential Disaster Declarations during this time period are not included (as reported in Gallagher [2013]).

and Reeves [2011], $Turndown_{ct}$ takes the same value for all counties in the state each year. $Turndown_{ct}$ is perfectly correlated for counties in the same state during the same year. The state-by-year spatial correlation in the approval of disaster requests will result in overly precise estimates for the coefficients in Equation 1, unless the spatial correlation is accounted for in the model (e.g. Moulton [1986]).

3 Presidential Vote Share Model Results

3.1 Replication

In Table 1 column 1 we replicate the preferred presidential vote share model in Gasper and Reeves [2011] using the datafile posted by the authors. A disaster declaration in the six months before an election increases the vote share for the party of the incumbent president by 0.48 percentage points, while a turndown decreases the vote share by 0.95 percentage points. The weather damage coefficient is negative. The county-level Presidential Disaster Declaration acceptance and denial decisions are strongly correlated by state and year (see Section 2.2). The table reports standard errors (in parentheses) that are robust to state-by-year spatial correlation. None of the coefficient estimates are statistically different from zero at conventional significance levels (probability values range from 0.15 to 0.39). The standard errors are approximately three to seven times smaller if we do not allow for the state-by-year spatial correlation.[7]

[7] The coefficient estimates are close to, but not identical to those in Gasper and Reeves [2011] Table 2 column 3. The reason is that we correct for two errors in the posted datafile. First, there are 1,852 repeated observations (i.e. rows of data) in the panel. Each repeated county-year observation has identical information for all variables as its duplicate. The panel includes 27,894 unique county-by-year observations after we drop the repeated observations. Second, approximately 5% of the disaster observations are incorrectly coded. We recode these observations. Please refer to the Appendix Section 1 for more details. The standard errors also differ from Gasper and Reeves [2011] Table 2 column 3. The main reason, as we note in the text, is because we allow for spatial correlation. Specifically, we cluster at the state-by-year level. Bootstrapped standard errors for the presidential analysis are similar in magnitude to the clustered standard errors (see Appendix Table 1).

The preferred model in Gasper and Reeves [2011] includes lagged values of the county vote share and county fixed effects. Coefficient estimates for the parameters of interest are inconsistent when both the lagged dependent variable and unit fixed effects are included as control variables (Nickell [1981]). The most straightforward solution is to estimate the model with either lagged vote share or county fixed effects (Angrist and Pischke [2008]). The fixed effect model is appropriate if we view the unobserved factors that affect voting as being mostly constant across elections. The lagged vote share model is preferred if there are important time-varying factors that affect voting preferences.

We show estimation results from the lagged vote share and county fixed effect specifications in Table 1 columns 2 and 3, respectively. The weather damage and turndown coefficients are somewhat smaller in magnitude in both specifications, relative to column 1. The disaster declaration coefficient is more stable, but less precisely estimated in the fixed effect regression. Overall, the lagged vote share model explains almost twice the variation in the data (using R-squared) as does the fixed effect model.

Table 1 columns 4-6 estimate the same models as columns 1-3, except that we use updated weather damage information from SHELDUS. Specifically, we recreate the six month county-level weather damage variable using monthly information from the 2018 SHELDUS (version 16).[8] Using the updated SHELDUS information has little effect on the estimated coefficients in the lagged vote share and county fixed effect regressions.

The bottom panel in the table reports the number of disaster and denied Presidential Disaster Declaration request (turndown) observations. We also list the number of disaster and turndown observations where the (six month)

[8] Gasper and Reeves [2011] rescale the 2009 SHELDUS information using county population when constructing the weather damage variable. The reason is that some of the damage information in SHELDUS is from Presidential Disaster Declaration-level cost records. Ostensibly, the disaster-level cost is divided equally among all counties impacted by the disaster. However, it is not always the case that there is reported cost information for all counties for each disaster. We do not rescale the 2018 SHELDUS information because not all of the weather damage information is due to disaster-level cost, and we are not always able to discern when the reported county damage is apportioned from a disaster-level cost. Healy and Malhotra [2009] report that their results are very similar regardless of whether they rescale the SHELDUS data using county population.

weather damage variable is zero. The weather damage variable is zero if there is no reported damage information for each of the six months before the election. The weather damage variable is also zero if one or more of the six months prior to the election has zero reported damage and the remaining months have missing information. The weather damage variable is zero for nearly one third of the disaster observations and one half of the turndown observations in the Gasper and Reeves [2011] replication panel (column 1). In the next section, we reanalyze the model using a panel that excludes all observations with missing weather damage, and only includes disaster request observations that report non-zero disaster damage.

Finally, the decision by Gasper and Reeves [2011] to assign *all* counties in a state a denied disaster request if there is a denied request for *any* county in the state dramatically overstates the actual number of turndown observations. Denied disaster requests, on average, involve a less severe weather event, and generally include far fewer proposed disaster counties than do approved disaster requests. We obtained the list of proposed disaster counties from 102 turndowns via a series of Freedom of Information Act (FOIA) requests.[9] The median number of counties included in a request is two. The average turndown only includes 9% of the counties in a state. More than 90% of the 4,698 turndown observations (column 1) in Gasper and Reeves [2011] are likely miscoded. The estimated turndown coefficient in Gasper and Reeves [2011] is identified off of a group of counties where the vast majority were never proposed by the governor for federal disaster assistance. We partially address this problem in our analysis by restricting the panel to only include disaster request counties where there is non-zero damage.

3.2 Reanalysis

In Table 2 we drop observations with missing weather damage information from the estimation panel. Gasper and Reeves [2011] use the 2009 SHELDUS database to construct the weather damage variable. The monthly damage es-

[9]See Appendix Section 2 for details.

timates from SHELDUS 2009 are (by user agreement) not posted by Gasper and Reeves [2011], and are no longer available for purchase. We use the 2018 SHELDUS database to determine whether the monthly weather damage information for each county is missing or reported as zero damage. We also use the updated 2018 SHELDUS information to define the weather damage variable in our main analysis. The Appendix Section 5 and Appendix Tables 2, 3, 5, and 6 show results using the original SHELDUS 2009 information.

We drop county observations that are not part of a Presidential Disaster Declaration request if there is missing information in SHELDUS (2018) in each of the six months prior to an election. We use a more restrictive inclusion rule for observations that are part of a disaster request. Our objective is to only include Presidential Disaster Declaration request observations in the panel if there is reported damage in the county at the time of the disaster.[10] Columns 1 and 2 require that there is non-missing damage reported (which could be zero) in the month of the disaster. In columns 3 and 4 we allow for a delay between when a county incurred weather damage and a disaster declaration or turndown. Disaster and turndown county observations are included in the panel if there is reported weather damage in the same month or either of the two preceding months.[11]

The estimated weather damage coefficient is relatively stable across the lagged vote share and county fixed effect models. All the damage coefficient estimates are statistically significant at conventional confidence levels (probability values range from 0.000 to 0.095). The weather damage coefficients are between six and eleven times larger in magnitude than the same specifications in Table 1. The weather damage coefficient for the county fixed effect model

[10]It is possible for the weather damage variable to have non-missing weather damage several months before the disaster request due to a weather event that is unrelated to the disaster request (since the weather damage variable is aggregated across six months). Appendix Table 7 columns 1 and 2 show results from a model that applies the same six month non-missing weather damage restriction to the panel for the disaster request counties.

[11]The number of days between the onset of a weather event and a disaster declaration or turndown is not always available. FEMA systematically posts this information for disaster declarations beginning in 1987. We calculate, using 1064 disasters from 1987-2007, that the median and mean delay is 16 days and 28 days, respectively. See Appendix Section 3 for details.

in column 4 implies a 1.5 percentage point reduction in the president's vote share for the disaster county with the median level of damage (conditional on reporting damage).

The estimated disaster assistance variables for the lagged vote share model are similar to those in Table 1 column 5. The disaster declaration and turndown estimates are smaller in magnitude in the fixed effect model relative to Table 1 column 6. None of the coefficients are statistically significant at conventional levels (probability values range from 0.14 to 0.95).

One striking feature of Table 2 is the number of disaster and turndown counties with zero reported damage in the six months before an election. We find it implausible that counties that are part of disaster requests have no reported weather damage. A Presidential Disaster Declaration is defined as when the weather damage is of "such severity and magnitude that effective response is beyond the capacities of the state and the affected local governments" (Daniels and Trebilcock [2006]). There are three explanations. First, the weather damage information is misreported. Counties with zero reported damage actually suffered severe damage. Second, there really is no weather damage and these counties should not have been included as part of a disaster request. Third, there is a lengthy time delay between the disaster damage and the disaster declaration or turndown. Regardless, the quasi-experimental research design that seeks to evaluate whether an electorate can separate the proactive actions of politicians from the random weather damage, makes no sense if there is zero reported weather damage.

In Table 3, we further restrict the sample by dropping disaster and turndown observations with zero dollars in reported weather damage. Table 3 columns 1 and 2 require that there is non-zero weather damage in the same month as the declaration or turndown. Columns 3 and 4 require that there is non-zero weather damage in the month of the event, or one of the two preceding months. Overall, the estimated weather damage and disaster declaration coefficients are slightly larger in magnitude in Table 3, as compared to the same specifications in Table 2. The estimated turndown coefficients are smaller in magnitude.

Figure 1 provides a graphical interpretation of the damage and declaration coefficients from Table 3 columns 1 and 2.[12] These models are our most restrictive specifications, and are least likely to suffer from misreported weather damage. We plot the estimated change in the presidential vote share for disaster counties with non-missing weather damage information. In our view, the most appropriate retrospective voting test is when voters experience damage from a natural disaster and the federal government provides disaster assistance.

The upward sloping line in each panel of Figure 1 calculates the lost vote share from weather damage. The damage line is drawn so that it spans the range of weather damage reported in the disaster counties (x-axis). Vote share is measured on the y-axis. The horizontal line shows the estimated electoral benefit of a disaster declaration. The shaded area around each line is the estimated 90% confidence interval.

Overall, the electorate is responsive. The electoral benefit of a disaster declaration does not offset the lost vote share due to weather damage in the typical county. The weather damage confidence interval is completely above the disaster declaration confidence interval for 94 percent of the counties in panel A, and 88 percent of the counties in panel B.

Figure 2 provides a graphical comparison of the reported weather damage coefficient from Gasper and Reeves [2011] and those from our analysis. The leftmost column plots the preferred point estimate from Gasper and Reeves [2011] (reproduced in Table 1 column 1). The next four columns in the lightly shaded area show our estimates from Table 3. The vertical lines represent the 90% confidence intervals. The reported weather coefficient in Gasper and Reeves [2011] is -0.028 (probability value 0.39). The imputation of missing weather damage as zero dollars biases the estimated damage coefficients towards zero. We find that the damage coefficient is consistently an order of magnitude more negative and statistically different from zero (probability values range from 0.000 to 0.095). We can statistically reject equivalence of the weather damage coefficient from Gasper and Reeves [2011] and our estimates that use the lagged vote share model.

[12] The figure replicates Figure 5 in Gasper and Reeves [2011].

4 Gubernatorial Vote Share Model Results

4.1 Replication

In Table 4 column 1 we replicate the preferred gubernatorial vote share model in Gasper and Reeves [2011] using the datafile posted by the authors. A disaster declaration in the six months before an election increases the vote share of the incumbent governor by 4.0 percentage points (probability value 0.026). A request for disaster assistance made by the governor, but turned down by the president, increases the governor's vote share by 2.6 percentage points (probability value 0.20). The weather damage coefficient is negative (probability value 0.11) and implies a 1.6 percentage point reduction in the governor's vote share in the median disaster county with non-zero weather damage.[13]

Table 4 columns 2 and 3 estimate the lagged vote share and county fixed effects models using the 2009 SHELDUS weather damage. Columns 5 and 6 estimate the same models using the 2018 SHELDUS weather damage. The estimated damage coefficient ranges between -0.05 and -0.24. The damage coefficients are larger in magnitude in the county fixed effects models, and when we use 2018 SHELDUS that has fewer missing weather observations. The disaster declaration coefficients are about half to two-thirds the size of those reported in Gasper and Reeves [2011]. The turndown coefficients are similar to Gasper and Reeves [2011] in the county fixed effect models, but somewhat smaller in magnitude in the lagged vote share models. Overall, all three coefficients are imprecisely estimated.

[13] The coefficient estimates are close to, but not identical to Gasper and Reeves [2011] Table 1 column 3. The reason is that we correct for disaster observations that are incorrectly coded. Please refer to Appendix Section 1 for more details. The standard errors also differ from Gasper and Reeves [2011] Table 1 column 3. The main reason, as we note in the text, is because we allow for spatial correlation.

4.2 Reanalysis

Tables 5 and 6 repeat the same analysis for the gubernatorial vote share, as we do for the presidential vote share in Tables 2 and 3. Four facts emerge. First, the estimated weather damage coefficients are similar to those in our presidential analysis for the county fixed effects models, but smaller in magnitude in the lagged vote share models. Second, the estimated disaster declaration coefficients are smaller than those reported in Gasper and Reeves [2011], but larger than our estimates in the presidential analysis. Third, the turndown coefficient estimates are an order of magnitude smaller than the disaster declaration estimates. The turndown coefficients are also much closer to zero than those reported in Gasper and Reeves [2011]. Fourth, only the disaster declaration coefficients are (mostly) statistically significant from zero at conventional confidence levels (probability values range from 0.027 to 0.300).

Figure 3 plots the estimated change in the gubernatorial vote share for disaster counties with non-missing weather damage information. As in Figure 1, we plot coefficients from the models that only include disaster request counties with positive weather damage in the month of the declaration or turndown (Table 6 columns 1 and 2). The evidence on retrospective voting is inconclusive. In contrast to our presidential analysis, there is no clear support for a responsive electorate. The large confidence intervals for the disaster declaration coefficients make definitive analysis difficult. The same is true if we were to plot the estimated turndown coefficients.

One striking finding of our analysis is that voters react to disaster requests very differently based on whether the governor's request is approved by the president. Voters only reward governors for their actions when a Presidential Disaster Declaration request is approved, even though the decision to approve the request is mostly outside of the governor's control.

Figure 4 provides a graphical comparison of the reported turndown and disaster declaration coefficients from Gasper and Reeves [2011], and our estimates from Table 6. The figure is similar to Figure 2, except that we plot the disaster declaration and turndown coefficients from the gubernatorial vote share analysis. The disaster declaration estimates from our analysis (circles in shaded region) are positive and statistically different from zero at conventional significance levels (probability values range from 0.027 to 0.095). The disaster declaration point estimates from the lagged vote share model are about half as large as the estimate in Gasper and Reeves [2011]. This finding is the strongest evidence in favor of an attentive electorate. Our estimates for a denied disaster request (squares in the shaded region), are close to zero and much smaller than the estimate in Gasper and Reeves [2011] plotted on the left of the figure.

5 Discussion

Over the past decade (or so) a new sub-literature has emerged that uses weather damage and the political response to natural disasters as a quasi-experiment to test theories of retrospective voting. The random timing and location of weather damage, along with the political response to assist disaster victims, provide an opportunity to more easily distinguish between retrospective voting theories. We reexamine the empirical evidence in Gasper and Reeves [2011], an early, seminal paper in this literature.

Gasper and Reeves [2011] analyze US gubernatorial and presidential elections from 1970-2006. The authors find that vote shares for incumbent politicians decrease in response to weather damage, but increase when incumbents help to facilitate post-disaster financial assistance. Overall, the authors conclude that the electorate is highly attentive. Their conclusion is bolstered by the finding that voters reward governors at almost equal rates when they request federal disaster assistance, regardless of whether the assistance is granted by the president.

We find little evidence in favor of an attentive electorate. Overall, our presidential model results imply a responsive electorate. The estimated presidential reelection vote share is lower (or indistinguishable from zero) in all disaster counties with non-missing damage information (Figure 1). Our gubernatorial model results are inconclusive (Figure 3). The large confidence intervals for our weather damage and disaster declaration estimates make definitive gubernatorial analysis impossible. Further, we find that voters only reward governors for their actions when a disaster request is approved, even though the decision to approve the request is mostly outside of the governor's control (Figure 4).

Two key factors most explain the difference in findings. First, the weather damage information from National Weather Service NCDC monthly Storm Data publications suffers from a high rate of missing data. The National Weather Service weather damage information is the a main source of data in SHELDUS, and are self-reported by individual weather stations. There is no mechanism in place to compel weather stations to report weather damage. Gasper and Reeves [2011] impute missing observations as zeros in their analysis. Remarkably, around a third of the counties with a Presidential Disaster Declaration in the panel have no reported weather damage. We drop these observations from our analysis.

Second, we allow for spatial correlation in weather damage and federal disaster assistance. The process which allocates county-level federal disaster assistance is highly correlated by state and year. In fact, due to data limitations and a coding decision, counties that are denied disaster assistance are perfectly correlated at the state-year level in Gasper and Reeves [2011]. Failure to allow for spatial correlation will dramatically overstate the statistical precision of the estimates from the reelection vote share models (e.g. Moulton [1986]). None of the main results reported in Gasper and Reeves [2011] are statistically different from zero at conventional significant levels after accounting for spatial correlation.

Our analysis casts doubt on the robustness of the findings in the nascent retrospective voting literature that uses weather damage and the political response as a quasi-experiment. The conclusions of Gasper and Reeves [2011] are mostly reversed under a complete case analysis that drop observations with missing or clearly mis-reported information, and which allows for the documented spatial correlation. Several other influential studies in the literature use the same weather damage data (Healy and Malhotra [2009]; Healy and Malhotra [2010]), or fail to allow for spatial correlation (Achen and Bartels [2004]).

Moving forward, we caution researchers against using the National Weather

Service NCDC monthly Storm Data publication (or SHELDUS) weather damage information without first carefully assessing the degree of non-reporting. All future studies using weather damage or disaster assistance information should account for the role of spatial correlation.

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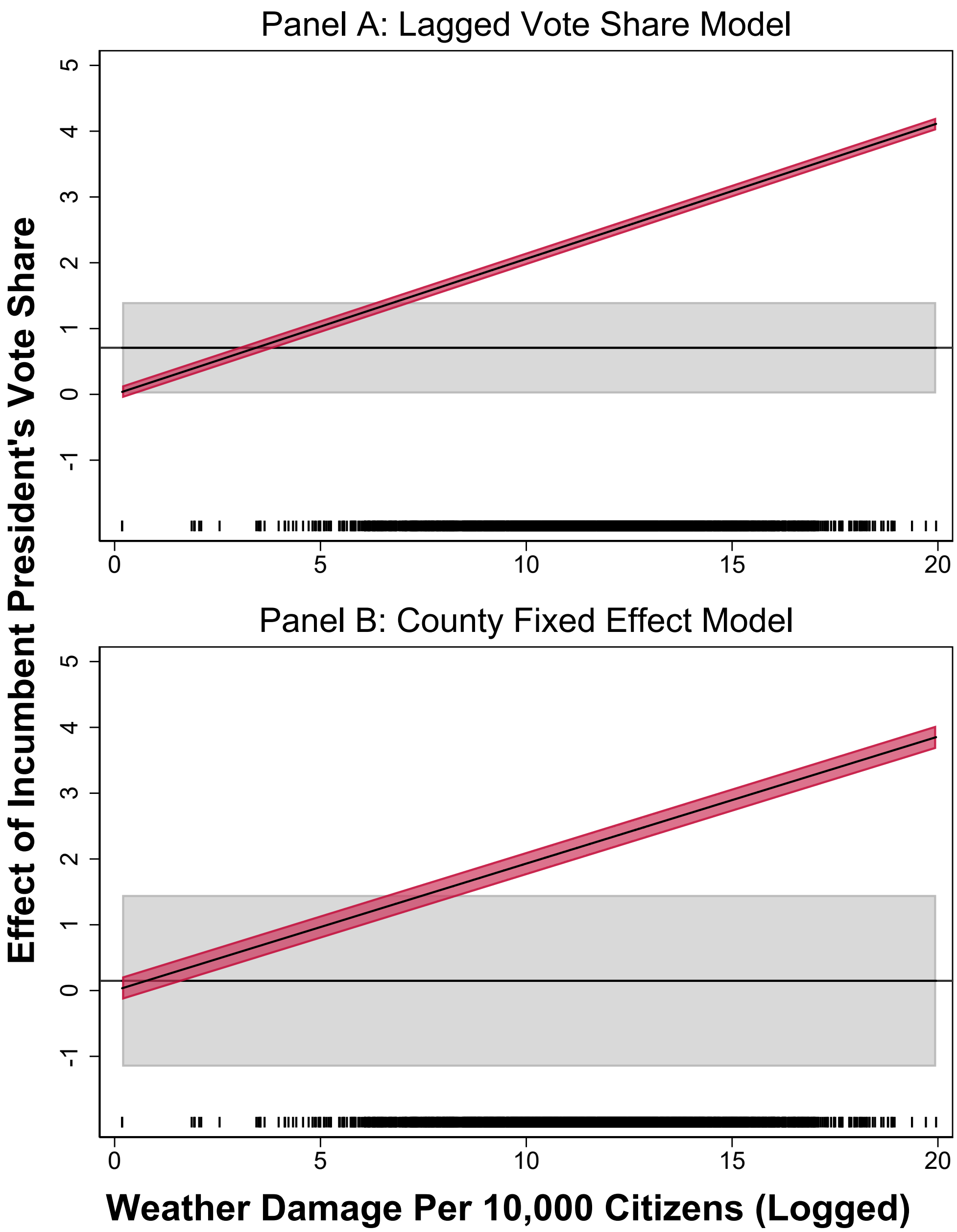
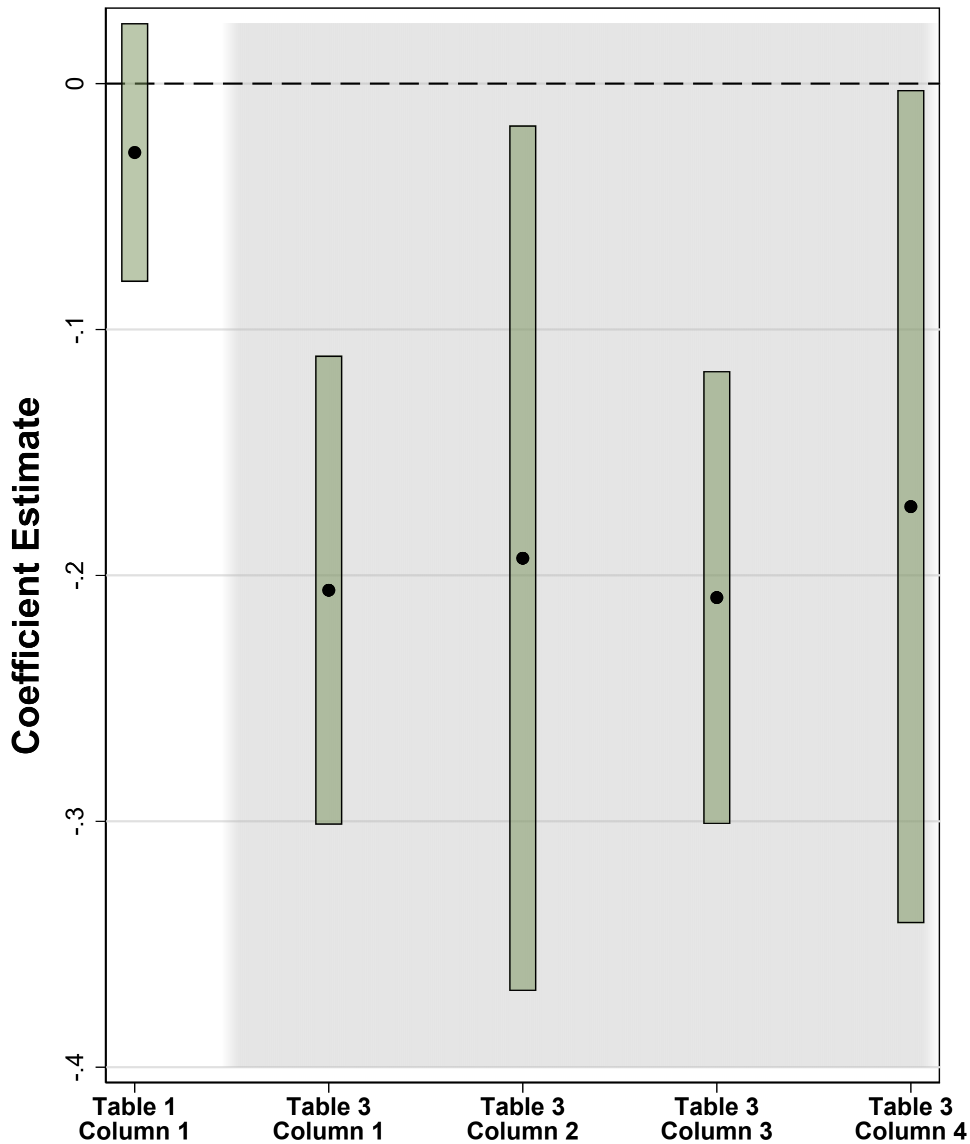
7 Figures and Tables

Figure 1: **Effect of Weather Damage and a Disaster Declaration on Incumbent Presidential Vote Share**



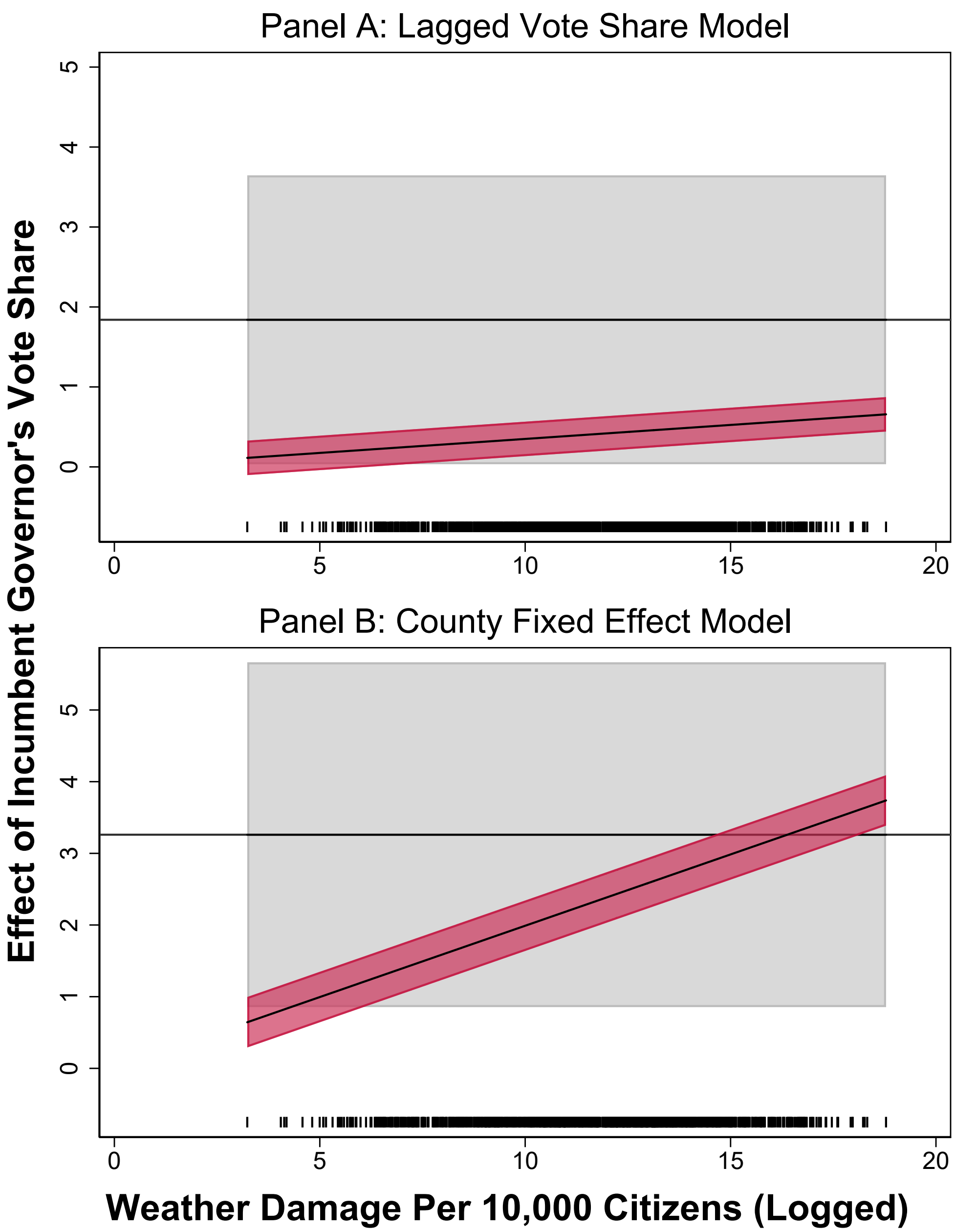
The figure plots the estimated change in the presidential vote share for disaster counties with non-missing weather damage information from the lagged vote share and county fixed effect models that only include disaster request counties with positive weather damage in the month of the declaration or turndown (Table 3 columns 1 and 2). The upward sloping line in each panel calculates the lost vote share from weather damage. The damage line is drawn so that it spans the range of weather damage reported in the disaster counties (x-axis). Vote share is measured on the y-axis. The horizontal line shows the estimated electoral benefit of a disaster declaration. The shaded area around each line is the estimated 90% confidence interval.

Figure 2: **A Comparison of How the Estimated Weather Damage Coefficients affect Presidential Vote Share**



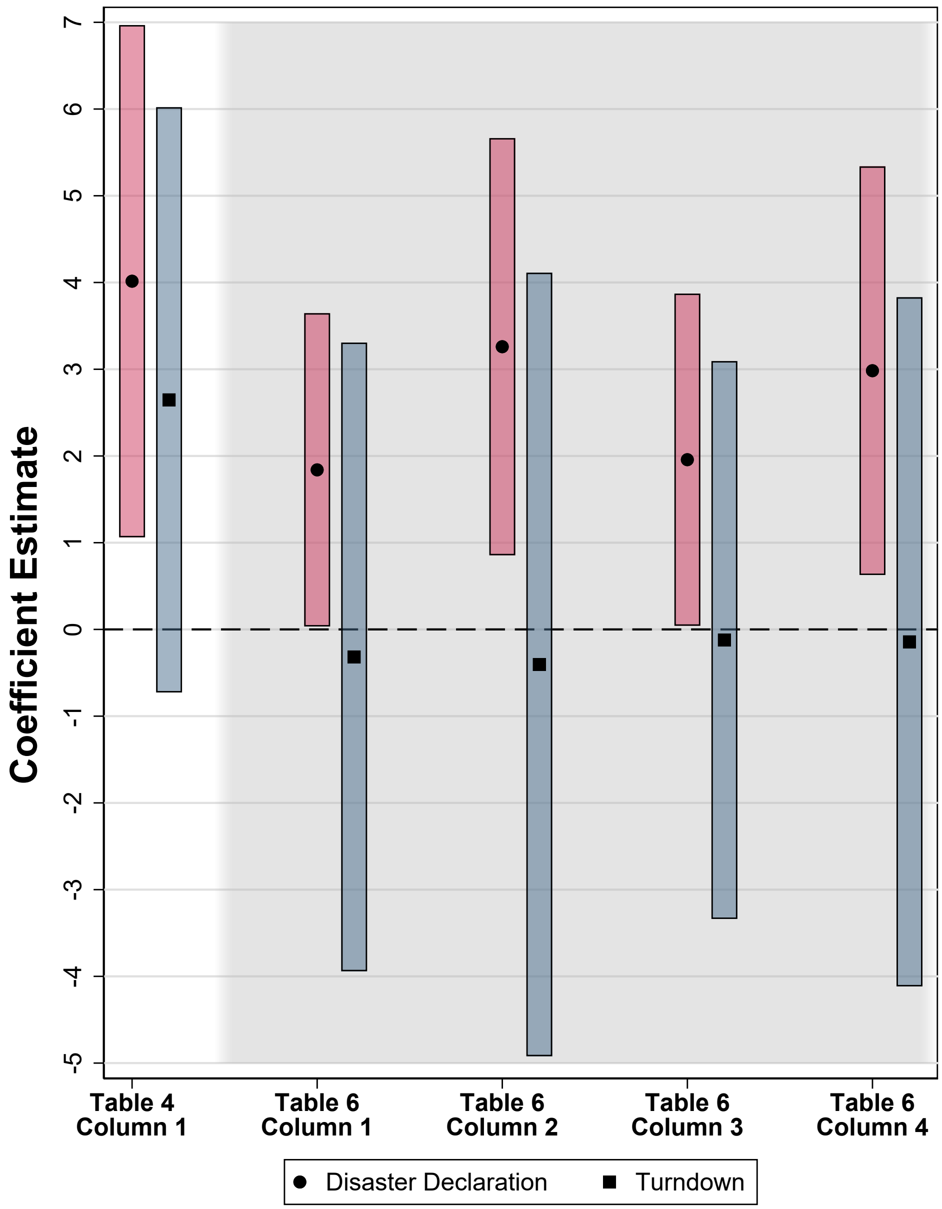
The figure provides a graphical comparison of the reported weather damage coefficient from Gasper and Reeves [2011] and those from our analysis. The leftmost column plots the preferred point estimate from Gasper and Reeves [2011] (reproduced in Table 1 column 1). The next four columns in the lightly shaded area show our estimates from Table 3. These specifications restrict the samples to best account for the weather damage measurement error. Vote share is measured on the y-axis. The vertical lines represent the 90% confidence intervals.

Figure 3: **Effect of Weather Damage and a Disaster Declaration on the Gubernatorial Reelection Vote Share**



The figure plots the estimated change in the gubernatorial vote share for disaster counties with non-missing weather damage information from the lagged vote share and county fixed effect models that only include disaster request counties with positive weather damage in the month of the declaration or turndown (Table 6 columns 1 and 2). The upward sloping line in each panel calculates the lost vote share from weather damage. The damage line is drawn so that it spans the range of weather damage reported in the disaster counties (x-axis). Vote share is measured on the y-axis. The horizontal line shows the estimated electoral benefit of a disaster declaration. The shaded area around each line is the estimated 90% confidence interval.

Figure 4: **A Comparison of How the Estimated Disaster Declaration and Turndown Coefficients affect Gubernatorial Vote Share**



The figure provides a graphical comparison of the reported turndown and disaster declaration coefficients from Gasper and Reeves [2011], and those from our analysis. The leftmost column plots the preferred point estimates from Gasper and Reeves [2011] (reproduced in Table 4 column 1). The next four columns in the lightly shaded area show our estimates from Table 6. These specifications restrict the samples to best account for the weather damage measurement error. Vote share is measured on the y-axis. The vertical lines represent the 90% confidence intervals.

Table 1: **Effect of Severe Weather and Disaster Assistance on Incumbent Presidential Vote Share, Replication of Gasper and Reeves (2011)**

Dependent Variable:	Incumbent Presidential Vote Share					
Damage Data:	SHELDUS 2009			SHELDUS 2018		
	GR Replication	Lagged Vote Share	County F.E.	GR Replication	Lagged Vote Share	County F.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Weather Damage	-0.028	-0.021	-0.013	-0.039	-0.028	-0.014
	(0.032)	(0.034)	(0.048)	(0.030)	(0.033)	(0.046)
Disaster Declaration	0.483	0.548	0.415	0.503	0.564	0.415
	(0.469)	(0.393)	(0.662)	(0.462)	(0.387)	(0.651)
Turndown	-0.949	-0.651	-0.799	-0.963	-0.662	-0.803
	(0.657)	(0.566)	(0.937)	(0.657)	(0.567)	(0.938)
Lagged Vote Share	X	X		X	X	
County Fixed Effects	X		X	X		X
Income	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
N	27,894	27,894	27,894	27,894	27,894	27,894
Disaster Obs.	3,132	3,132	3,132	3,132	3,132	3,132
Disaster Obs. with Damage = 0	1,017	1,017	1,017	687	687	687
Turndown Obs.	4,698	4,698	4,698	4,698	4,698	4,698
Turndown Obs. with Damage = 0	2,343	2,343	2,343	1,765	1,765	1,765
R^2	0.816	0.793	0.415	0.816	0.793	0.415

The bottom panel reports the number of Presidential Disaster Declaration observations and denied Presidential Disaster Declaration observations (Turndowns) where the six month weather damage variable is zero (i.e. all six months have non-reported information or report zero damage). Standard errors that allow for state-by-year spatial correlation are in parentheses. Data sources: Federal Emergency Management Agency (FEMA), Public Entity Risk Institute (PERI), Special Hazards and Losses Database for the United States (SHELDUS), US Decennial Census.

Table 2: **Effect of Severe Weather and Disaster Assistance on Incumbent Presidential Vote Share, Complete Case Analysis**

Dependent Variable:	Incumbent Presidential Vote Share			
Missing Rule:	Disaster Month		Disaster Month or 2 Prior Months	
Specification:	Lagged Vote Share	County F.E.	Lagged Vote Share	County F.E.
	(1)	(2)	(3)	(4)
Weather Damage	-0.191	-0.184	-0.181	-0.154
	(0.055)	(0.100)	(0.051)	(0.092)
Disaster Declaration	0.530	0.050	0.558	0.306
	(0.419)	(0.749)	(0.377)	(0.661)
Turndown	-0.709	-0.109	-0.814	-0.575
	(0.662)	(1.171)	(0.547)	(1.022)
Lagged Vote Share	X		X	
County Fixed Effects		X		X
Income	X	X	X	X
Year Fixed Effects	X	X	X	X
N	16,987	16,987	18,218	18,218
Disaster Obs:	1,567	1,567	2,272	2,272
Disaster Obs. with Damage = 0	71	71	86	86
Turndown Obs.	1,762	1,762	2,428	2,428
Turndown Obs. with Damage = 0	41	41	130	130
R^2	0.805	0.467	0.806	0.456

The table shows estimates from the presidential lagged vote share and county fixed effect models using data panels that only include observations (counties) that report non-missing weather damage information for at least one of the six months before the election. Columns 1 and 2 further restrict the panel to only include Presidential Disaster Declaration request counties that report weather damage at the time of the Disaster Declaration or Turndown (columns 3 and 4 relax this restriction to include the two prior months). The bottom panel reports the number of Disaster Declaration observations and denied Disaster Declaration observations (Turndowns) where the six month weather damage variable is zero (i.e. reported as zero for at least one of the six months, and missing or zero for the other months). Standard errors that allow for state-by-year spatial correlation are in parentheses. Data sources: Federal Emergency Management Agency (FEMA), Public Entity Risk Institute (PERI), Special Hazards and Losses Database for the United States (SHELDUS), US Decennial Census.

Table 3: **Effect of Severe Weather and Disaster Assistance on Incumbent Presidential Vote Share, Exclude Disaster Request Counties with Zero Reported Weather Damage**

Dependent Variable:	Incumbent Presidential Vote Share			
Missing Rule:	Disaster Month		Disaster Month or 2 Prior Months	
Specification:	Lagged Vote Share	County F.E.	Lagged Vote Share	County F.E.
	(1)	(2)	(3)	(4)
Weather Damage	-0.206	-0.193	-0.209	-0.172
	(0.058)	(0.107)	(0.056)	(0.103)
Disaster Declaration	0.708	0.148	0.671	0.363
	(0.422)	(0.793)	(0.383)	(0.698)
Turndown	-0.567	-0.083	-0.483	-0.214
	(0.686)	(1.202)	(0.576)	(1.095)
Lagged Vote Share	X		X	
County Fixed Effects		X		X
Income	X	X	X	X
Year Fixed Effects	X	X	X	X
N	16,722	16,722	17,862	17,862
Disaster Obs:	1,431	1,431	2,151	2,151
Disaster Obs. with Damage = 0	0	0	0	0
Turndown Obs.	1,624	1,624	2,181	2,181
Turndown Obs. with Damage = 0	0	0	0	0
R^2	0.804	0.467	0.805	0.456

The table shows estimates from the presidential lagged vote share and county fixed effect models using data panels that only include observations (counties) that report non-missing weather damage information for at least one of the six months before the election. Columns 1 and 2 further restrict the panel to only include Presidential Disaster Declaration request counties that report non-zero weather damage at the time of the Disaster Declaration or Turndown (columns 3 and 4 relax this restriction to include the two prior months). The bottom panel reports the number of Disaster Declaration observations and denied Disaster Declaration observations (Turndowns) where the six month weather damage variable is zero (i.e. reported as zero for at least one of the six months, and missing or zero for the other months). Standard errors that allow for state-by-year spatial correlation are in parentheses. Data sources: Federal Emergency Management Agency (FEMA), Public Entity Risk Institute (PERI), Special Hazards and Losses Database for the United States (SHELDUS), US Decennial Census.

Table 4: **Effect of Severe Weather and Disaster Assistance on Incumbent Gubernatorial Vote Share, Replication of Gasper and Reeves (2011)**

Dependent Variable:	Incumbent Gubernatorial Vote Share					
Damage Data:	SHELDUS 2009			SHELDUS 2018		
	GR Replication	Lagged Vote Share	County F.E.	GR Replication	Lagged Vote Share	County F.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Weather Damage	-0.133	-0.051	-0.161	-0.209	-0.113	-0.239
	(0.084)	(0.078)	(0.108)	(0.088)	(0.079)	(0.112)
Disaster Declaration	4.015	1.952	2.531	4.167	2.085	2.684
	(1.795)	(1.449)	(1.689)	(1.763)	(1.429)	(1.664)
Turndown	2.647	1.838	2.577	2.628	1.837	2.555
	(2.051)	(1.868)	(2.504)	(2.029)	(1.848)	(2.484)
Lagged Vote Share	X	X		X	X	
County Fixed Effects	X		X	X		X
Income	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
N	15,580	15,580	15,580	15,580	15,580	15,580
Disaster Obs.	1,586	1,586	1,586	1,586	1,586	1,586
Disaster Obs. with Damage = 0	468	468	468	345	345	345
Turndown Obs.	2,849	2,849	2,849	2,849	2,849	2,849
Turndown Obs. with Damage = 0	1,324	1,324	1,324	984	984	984
R^2	0.527	0.430	0.216	0.529	0.431	0.219

The bottom panel reports the number of Presidential Disaster Declaration observations and denied Presidential Disaster Declaration observations (Turndowns) where the six month weather damage variable is zero (i.e. all six months have non-reported information or report zero damage). Standard errors that allow for state-by-year spatial correlation are in parentheses. Data sources: Federal Emergency Management Agency (FEMA), Public Entity Risk Institute (PERI), Special Hazards and Losses Database for the United States (SHELDUS), US Decennial Census.

Table 5: **Effect of Severe Weather and Disaster Assistance on Incumbent Gubernatorial Vote Share, Complete Case Analysis**

Dependent Variable:	Incumbent Gubernatorial Vote Share			
Missing Rule:	Disaster Month		Disaster Month or 2 Prior Months	
Specification:	Lagged Vote Share	County F.E.	Lagged Vote Share	County F.E.
	(1)	(2)	(3)	(4)
Weather Damage	-0.028	-0.209	-0.070	-0.263
	(0.121)	(0.199)	(0.118)	(0.186)
Disaster Declaration	1.429	2.825	1.824	2.842
	(1.377)	(1.569)	(1.220)	(1.445)
Turndown	-0.014	-0.325	0.135	0.181
	(2.138)	(2.645)	(1.924)	(2.359)
Lagged Vote Share	X		X	
County Fixed Effects		X		X
Income	X	X	X	X
Year Fixed Effects	X	X	X	X
N	9,690	9,690	10,377	10,377
Disaster Obs:	886	886	1,241	1,241
Disaster Obs. with Damage = 0	66	66	91	91
Turndown Obs.	1,225	1,225	1,611	1,611
Turndown Obs. with Damage = 0	38	38	60	60
R^2	0.406	0.343	0.410	0.327

The table shows estimates from the gubernatorial lagged vote share and county fixed effect models using data panels that only include observations (counties) that report non-missing weather damage information for at least one of the six months before the election. Columns 1 and 2 further restrict the panel to only include Presidential Disaster Declaration request counties that report weather damage at the time of the Disaster Declaration or Turndown (columns 3 and 4 relax this restriction to include the two prior months). The bottom panel reports the number of Disaster Declaration observations and denied Disaster Declaration observations (Turndowns) where the six month weather damage variable is zero (i.e. reported as zero for at least one of the six months, and missing or zero for the other months). Standard errors that allow for state-by-year spatial correlation are in parentheses. Data sources: Federal Emergency Management Agency (FEMA), Public Entity Risk Institute (PERI), Special Hazards and Losses Database for the United States (SHELDUS), US Decennial Census.

Table 6: **Effect of Severe Weather and Disaster Assistance on Incumbent Gubernatorial Vote Share, Exclude Disaster Request Counties with Zero Reported Weather Damage**

Dependent Variable:	Incumbent Gubernatorial Vote Share			
Missing Rule:	Disaster Month		Disaster Month or 2 Prior Months	
Specification:	Lagged Vote Share	County F.E.	Lagged Vote Share	County F.E.
	(1)	(2)	(3)	(4)
Weather Damage	-0.035	-0.199	-0.067	-0.253
	(0.131)	(0.214)	(0.131)	(0.206)
Disaster Declaration	1.840	3.260	1.957	2.983
	(1.098)	(1.462)	(1.164)	(1.432)
Turndown	-0.317	-0.404	-0.122	-0.143
	(2.203)	(2.746)	(1.955)	(2.415)
Lagged Vote Share	X		X	
County Fixed Effects		X		X
Income	X	X	X	X
Year Fixed Effects	X	X	X	X
N	9,480	9,480	10,183	10,183
Disaster Obs:	738	738	1,129	1,129
Disaster Obs. with Damage = 0	0	0	0	0
Turndown Obs.	1,160	1,160	1,527	1,527
Turndown Obs. with Damage = 0	0	0	0	0
R^2	0.410	0.346	0.411	0.331

The table shows estimates from the gubernatorial lagged vote share and county fixed effect models using data panels that only include observations (counties) that report non-missing weather damage information for at least one of the six months before the election. Columns 1 and 2 further restricts the panel to only include Presidential Disaster Declaration request counties that report non-zero weather damage at the time of the Disaster Declaration or Turndown (columns 3 and 4 relax this restriction to include the two prior months). The bottom panel reports the number of Disaster Declaration observations and denied Disaster Declaration observations (Turndowns) where the six month weather damage variable is zero (i.e. reported as zero for at least one of the six months). Standard errors that allow for state-by-year spatial correlation are in parentheses. Data sources: Federal Emergency Management Agency (FEMA), Public Entity Risk Institute (PERI), Special Hazards and Losses Database for the United States (SHELDUS), US Decennial Census.