Do Voters Appreciate Responsive Governments? Evidence from Indian Disaster Relief*

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ABSTRACT:

Using rainfall, public relief, and election data from India, we examine how governments respond to adverse shocks and how voters react to these responses. The data show that voters punish the incumbent party for weather events beyond its control. However, we find evidence that fewer voters punish the ruling party when the party responds vigorously to the crisis. Moreover, severe crises are associated with increased voter sensitivity to disaster assistance. These results are consistent with models of government accountability, and provide an explanation for Amartya Sen's claim that democratic governments respond better to salient emergencies than to less conspicuous ones. Even so, the results suggest that even the most responsive government will fare worse in the subsequent election than had there been no disaster.

I. Introduction

In a functioning democracy, politicians' ability to win reelection declines when they perform poorly. This idea fits well with models of political accountability. Recent evidence suggests, however, that voters may punish politicians even for events outside their control. This behavior may violate standard models of democratic accountability, and has been advanced as evidence of voter irrationality.

Yet, not all bad shocks are bad for politicians. Rudolph Giuliani's political career, wrote *The New York Times Magazine* in September 2007, "is built atop the rubble of the twin towers." Giuliani's leadership following the terrorist attacks, according to most accounts, catapulted the former mayor into a presidential run. Similarly, the "main source of [Russian President Vladimir] Putin's popularity," wrote Richard Haass in 2000, was the perception that the war against the Chechen rebels was going well.

In this paper, we use weather crises to identify the relationship between government response and electoral decisions. Specifically, we look at the decisions that Indian voters make in provincial elections, using the quality of the monsoon rains as an exogenous shock to welfare. We find that voters do indeed punish politicians following adverse weather events, but that the degree of punishment depends critically on the quality of the ruling party's response: those distributing greater amounts of relief aid suffer smaller subsequent electoral losses.

We motivate our analysis with a simple principal-agent view of political accountability, in which voters observe their own welfare, the public and exogenous welfare shock, as well as the government response. Rational voters can filter the observed shock from the government's performance, and do not punish politicians for bad luck. However, if the government's ability is more accurately revealed during a crisis, rational voters may "correctly" vote against incumbent politicians following adverse weather if they respond poorly. Finally, if voters are irrational or boundedly rational, they may punish politicians simply because a negative shock has occurred, either ignoring or insufficiently weighing the government's response.

Our paper builds on recent work examining voters' response to adverse shocks. Achen and Bartels (2004) find that leaders are punished for droughts, floods, and even shark attacks that occur under their watch. Healy (2008) finds that American voters systematically punish the incumbent party for tornado damage in election years. In a similar vein, Wolfers (2006) and Leigh (2004) show that incumbent politicians are punished for movements in the economy outside their plausible sphere of influence. None of these papers, however, includes measures of government response in their descriptions of voter decisions.

The determinants of crisis relief, on the other hand, have received some attention. Besley and Burgess (2002) show that state governments in India are responsive to agricultural and weather-induced catastrophes, but the degree of response depends on the sophistication of the voters. Specifically, they find that state governments increase public food distribution and calamity relief expenditures more when their electorates are characterized by higher literacy rates and greater newspaper circulation. This research is in the tradition of Amartya Sen and others who have sought to understand the prevention and resolution of food crises with a particular focus on India (Sen 1981, Drèze and Sen, 1989). Sen observed that democracies are better at responding to "those disasters that are easy to understand and where sympathy can take a particularly immediate form" than to less salient deprivations (1999, p. 154). Sen's argument suggests either that some governments have limited awareness of certain crises or that public accountability is crucial to creating the incentives that lead to vigorous government response. Some evidence from the United States suggests that the importance of electoral incentives may be the crucial factor; Garrett and Sobel (2003) found that half of federal emergency relief appears to be driven by a given state's importance in winning presidential elections.

The fact that governments respond to electoral incentives suggests that voters reward at least some types of government response efforts. At the same time, the fact that governments may respond less well to less visible crises certainly suggests limitations to voters' abilities to hold governments accountable. In this paper, we use electoral data from India to test hypotheses relating to how effectively voters hold governments accountable for crisis response. We note several advantages of our setting. India's size and history yield a large sample size: there have been over 21,000 elections in over 25 states, spanning nearly a quarter century. Agriculture is critically important to India's economy (employing over half the nation's population throughout our sample), and rainfall shocks are measured accurately. This enables extraordinarily precise estimation, as well as the flexibility to explore heterogeneous shocks and treatment effects.

Our results are consistent with both the electoral accountability literature as well as the voter irrationality literature. We establish that rainfall is an important determinant of agricultural output and that relief does flow to areas hardest hit by crisis events. We then confirm the basic findings of Achen and Bartels (2004) and Healy (2008) in the Indian context. We show that, on average, incumbent parties that run for re-election get punished for bad weather, losing more than 3 percent of the vote for each standard deviation rainfall in their district deviates from the optimum. We find suggestive evidence that this effect is stronger in farming districts, where rainfall has a larger impact on income, and weaker in districts with a higher literacy rate, where voters may be more sophisticated and less likely to blame politicians for events beyond their control.

Next, we test whether voters reward governments that increase disaster spending in response to extreme rainfall. Our results are strong and significant: incumbents fare better when they respond to a crisis with emergency relief. However, we estimate that governments that respond to crises with an average increase in relief spending are able to make up votes equivalent to only one seventh the punishment from having presided during a crisis in the first place. We argue that these results are not driven by the omitted variable of government competence by controlling for observable characteristics of government competence as well as the government's response to crises earlier in the election cycle where voter recall is much weaker.

Finally, we investigate nonlinear dynamics around voting and weather crises. When we restrict the analysis to extreme weather events (rainfall in the worst decile for crop production) we find that a 2.5-times average increase in relief spending can make up all the bad luck of presiding over a drought. Importantly, we find that governments are much more generous with relief spending to regions hit by the worst decile of weather shocks than they are to the second-worst decile – even though there is substantial crop loss under both scenarios. We argue this is likely to be motivated by biases in voter response: votes are more than twice as sensitive to relief spending during these extreme weather events than they are to relief spending during the less salient crises.

Overall, these results tie together the findings of the literature on government accountability and voter irrationality. In democratic contexts, governments respond to crises with government-supplied relief, but the degree to which they do so depends on the likely electoral return. Indian voters, on average, punish their leaders for events beyond their control, a finding consistent with voter irrationality. However, the degree of this punishment is reduced for improved government responsiveness to those events. Moreover, the vote-increasing power of a competent response is strongest during conspicuous crises, supporting Sen's view that democracies are better at monitoring disasters than quiet deprivation.

The rest of the paper is organized as follows. Section II summarizes the context of the political system in India and related research. Section III describes our data set and empirical specifications. Section IV details the main results of our analysis on crop yields, relief spending, and voting outcomes. Section V examines whether government and voter behavior differs during especially severe climatic events. Section VI concludes.

II. Politics in India

Previous Research on Indian Elections

Several studies have exploited the richness of Indian electoral data. Linden (2004) uses a regression-discontinuity design to test for incumbency advantage in Indian national elections, finding that candidates enjoyed an incumbency advantage prior to 1991, while suffering from an incumbency disadvantage in the subsequent period. Khemani (2001) examines voter behavior in state and national elections and finds that voters evaluate state politicians based on economic growth over their representative's five-year term; in contrast, when evaluating national elections, they are influenced primarily by recent economic growth.

Perhaps the paper most closely related to the present draft is Afzal (2007), which studies rainfall and voting in South Asia. Afzal develops a model in which politicians who own land face a tradeoff between political effort and farm labor. When there is an incumbency disadvantage and good rainfall, politicians will not bother to govern well given the opportunity cost of agricultural production. She tests this model using development fund spending in Pakistan, and variation in the profession of elected members of India's lower parliament, finding support for the model – in other words, the rainfall/re-election link is sensitive to the incumbency (dis)advantage of the period.

This paper differs from Afzal in several ways. We focus on state, rather than federal elections. Our time panel is substantially longer, and because state elections are staggered, we can control for national political trends by including state fixed-effects. Most importantly, drought and flood relief spending is organized at the state level. The goal of our paper is not to test whether voters act rationally or irrationally, but rather to better understand the incentives faced by electoral officials, how politicians react to these incentives, and how voters in turn respond.

Political Context

In this paper we focus on state-level elections. State governments are responsible for most public goods in India, including agricultural infrastructure, health, and education. Importantly, they are also responsible for spending on disaster relief and distributing food grains (Khemani 2007). India has a federal system of government, with a bicameral national legislature, but typically unicameral state legislatures.[1] The chief executive of the state is the Chief Minister, who is chosen by the parliament. States also have titular governors, whose powers are mainly ceremonial.

Our main measure of state responsiveness is state spending on disaster relief – these amounts are reported in state budgets, and include both "planned" and "unplanned" expenditure. The former is either allocated ex-ante into the budget as a contingency, or included to pay for ongoing disaster relief.

Elections in India function on a first-past-the-post system, with a seat going to the candidate who gets a plurality of votes. The number of seats per state ranges from 19 to 406, with an average of 136. Following the election, the governor of the state invites the party with the largest number of seats to form a government. If the party manages to form a majority, it becomes the ruling party. If not, the governor invites the next-largest party to form a ruling coalition.

[1] A few states have upper houses, with indirect elections; for those states, we study the more important chamber, the popularly elected lower house.

The first state and federal elections were held in 1951, shortly after the promulgation of India's constitution. Parliamentary elections are scheduled to occur at five-year intervals. While state and federal elections were once generally synchronized, over time they have become less so as states hold early elections.

As in other parliamentary systems, elections may be called if the government loses a no-confidence vote. Alternatively, under article 356 of the constitution, the central government can declare "President's Rule," dismiss the state legislature and executive, and appoint a governor. This is meant to occur when "the Government of the State cannot be carried on in accordance with the provisions of this Constitution."[2]

Campaign finance is relatively restricted in India, as compared to the United States. The nominal limits on spending are very low, less than US$1,000 for the period covered in our data (Sridharan, 1999). While certainly candidates and parties often spend more than the legal limit, in general, hard-dollar spending is of limited importance. In contrast, politically-motivated budget manipulation, and government-owned bank lending are important features of Indian elections that may aid incumbents seeking re-election. (See Khemani, 2004, and Cole, 2008, for examples.) In Russia, such manilupations have been shown to aid re-election (Akhmedov and Zhuravskaya, 2004).

Politics and parties

The Indian National Congress Party, which led the independence movement, initially dominated Indian politics. It won a majority in every federal election until 1977, and captured many state assemblies as well. In addition to Congress, there are several other major national parties (including the Communist Party of India and the Hindu-nationalist Bharatiya Janata Party) and a host of recognized state parties.

There are limited barriers to entry in Indian electoral contests, and the number of candidates running for office ranges from 1 to over 10.[3] During the period covered by our

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[2] While this clause has been invoked over 100 times, a federal government report argued that the vast majority of cases were warranted, either because of state reorganization or the collapse of the state ruling coalition (National Commission to Review the Working of the Constitution, 2002). Eighteen of these cases, occurring in 1977 and 1980, were deemed clearly abusive, with the central government dismissing hostile state governments, while 13 were viewed as possibly abusive (Section 8.16).

[3] The constitution mandates that each state reserve a share of seats for scheduled tribes and scheduled castes (the *dalits*, or untouchables).

data, constituency boundaries were stable, allowing us to match constituencies over time and thus identify the political affiliation of the incumbent.[4]

Chhiber and Kollman (1998) find that while the number of state and national parties fluctuates, in any given electoral district there are usually two effective parties. State parties may form (informal) coalitions prior to elections, dividing up the constituencies in which they run candidates so as not to compete with other members of the presumed post-election coalition. Because the number of competitive parties within a constituency is typically only two, we simplify coalitional analysis by coding parties that are part of the ruling coalition as "majority," with all others serving as "opponents."[5]

III. Data and Empirical Specification

Our dataset contains information about the voting decisions of 1.58 billion voters in 21,532 electoral competitions in 28 Indian states over the period 1977-1999. The unit of observation is, unless otherwise noted, the administrative district-election interaction. Voting outcomes are aggregated up from the constituency-level to the district level.[6] We augment this dataset with information about rainfall, crop yields, population characteristics, and disaster relief spending.

Electoral data, from the Election Commission of India, provide for every election candidate the name, sex, party affiliation, and number of votes won. There are 594 administrative districts. A district is an administrative unit within a state roughly equivalent to a U.S. county; the number of constituencies in a district ranges from 1 to over 50, with a median of 5. We begin our analysis in 1977, after which Congress victory was no longer assured.

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[4] Of the 21,532 elections in our data, we are able to identify the incumbent party in 17,744 elections. We cannot identify the incumbents following state political reorganizations, which resulted in the creation of entirely new legislative assemblies for the new states.

[5] Information on coalitions is not officially disseminated by any source we know of. Newspaper articles from the *Times of India* describing the outcome of each election were used to group parties into coalitions.

[6] The original unit of observation for our analysis was the electoral constituency, rather than the administrative district. However, because there are no time-varying regressors at the sub-district level, we choose the more conservative approach of aggregating results to the district * election year.

Rainfall data, gathered by Willmott and Matsuura (2001), provide monthly aggregate rainfall interpolated at the 0.5 degree level, or approximately 30 miles, which we match to districts.[7] We account for spatial correlation of error terms by clustering results at the state-election level; the results are robust to clustering at the state level (available upon request). Data on agricultural output, from Sanghi, Kumar, and McKinsey (1998), provide the quantity, yield, and price for 25 of the most common agricultural crops in India. The dataset runs from 1950 to 1994; for the subsequent years, we use an updated version created by Rohini Pande.[8]

Table 1 describes the summary statistics from our datasets. An average state election in our dataset had 156 seats. The most successful party won, on average, 56 percent of the seats in a state election. Only a plurality is necessary to win a constituency, and the winning candidate on average received approximately 48 percent of the vote. Finally, the incumbent ruling coalition won, on average, only 35 percent of votes in a constituency.

Panel B describes the weather data. We use as our main measure of rainfall the total amount of rain falling in a district from June 1 to September 30, which roughly approximates the *Kharif* growing season. This monsoon period is the most important for agriculture. The average of mean rainfall across districts is approximately 995mm, with a standard deviation of 667mm. Within a district, there is less variation: the median district receives an average rainfall of 890mm, with a standard deviation of 231mm.

Panel C gives mean disaster expenditure per person in constant 1998 rupees, using a deflator from the Reserve Bank of India; this amounted to 10 rupees per person (with a standard deviation of 12 rupees), equivalent to approximately $0.32 today.

We adopt a general approach to map the quality of the monsoon to the value of agricultural output, using simple transformations of total rainfall occurring during the

[7] To match districts to rainfall, we calculate the centroid of each district using a 2001 GIS map. We then define a district's rainfall pattern as the grid point that is closest to the centroid. While this induces some measurement error, we are confident that the match is close.

[8] Indian districts are periodically re-organized, typically by dividing one district into two districts. Thus, the number of districts increases over time. We map our electoral data and rainfall data to the most recent district boundaries (594 districts). The agricultural dataset was collected in a manner that maintains consistent data over the period 1950-1994, and therefore contains 272 districts per year.

monsoon period.[9] The first of our two measures of weather, *weather*$_{dt}$, is normalized rainfall, $\frac{Rain_{dt} - \overline{Rain_d}}{s_d}$, where $Rain_{dt}$ is the number of millimeters of rainfall during the kharif season, and s_d is the standard deviation of annual kharif rainfall within the district. The relationship between normalized rainfall and outcomes need not be linear: a quadratic specification allows for the possibility that excess rainfall may cause crop damage.[10]

Our second measure is the absolute deviation of normalized rainfall from the district optimum: $\left|\frac{Rain_{dt} - \overline{Rain_d}}{s_d} - 1\right|$. This second measure is meant to represent the degree to which rain varies from the optimal amount, measured in standard deviations from the district mean. The next section demonstrates that the optimal level of rainfall is about one standard deviation above the mean.

We are interested in the effect of weather events on three general classes of outcomes: crop yield, government response, and voting. The primary contribution of this paper is the elucidation of the relationship between weather, government response, and electoral response to both weather and government action. Of course, necessary first steps are to verify that weather indeed affects crop yields, and that governments respond to natural disasters.

We measure the relationship between rainfall and crop yield with the following regression, run on a panel of 272 districts over 32 years:

$$(1) \qquad Yield_{dt} = \alpha + \gamma_d + \tau_t + \beta * Weather_{dt} + e_{dt}$$

where $Yield_{dt}$ is a measure of the log value of a district's crop output, and include fixed effects for district, γ_d, and year, τ_t. We weight the regressions by the number of votes in the district; the results are robust to non-weighted specifications (available upon request). As described previously, we use two different measures of $weather_{dt}$ to ensure that our

[9] While different crops have different rainfall requirements, farmers grow crops that are appropriate for their climatic region; we thus believe the most logical analysis maps total monsoon rainfall to crop output.
[10] Non-parametric estimation, not reported, suggests that a quadratic specification provides a good approximation of the true relationship between rainfall and voting, expenditures, and crop yield.

results are robust. Agronomic models indicate yield increases in rain up to an optimal point, at which point yields fall, as excess rainfall damages the crops. Thus, using the second measure, the absolute normalized deviation of rain from the optimal rainfall, we expect a negative and monotonic relationship.

Our measurement of the relationship between rainfall and relief is similar. We regress the log of state expenditure on disaster relief, at the state level, on total state expenditure (excluding relief expenditure), state and year fixed effects, and lagged weather.

$$(2) \qquad Relief_{st} = \alpha + \gamma_s + \tau_t + \eta * TotalSpending_{st} + \beta * \overline{Weather}_{st-1} + e_{st}$$

In the above equation, we take the mean of the weather variable across the state in a given year. We lag weather because the Indian fiscal year ends on March 31. Thus, relief spending for the 2000 fiscal year, represents spending in the twelve months from April 1999 to March 2000. We therefore relate relief spending from April 1999 to March 2000 to weather from May 1999 to October 1999, the most recent monsoon season. We expect our coefficients on weather to be the opposite from those in equation (1): more extreme weather should generate higher relief spending.[11]

Finally, we estimate the relationship between weather and voting with the following equation:

$$(3) \qquad VoteShare_{dct} = \alpha + \gamma_d + \tau_t + \beta * weather_{dt-1} + e_{dt}$$

$VoteShare_{dct}$ is the vote share in a constituency c for the candidate from the incumbent ruling party. We use the previous year's weather, as the main kharif season is from June to September, while the elections typically occur in February and March. Thus the rain in

[11] Many states in India have a second growing season, called *Rabi*, in the winter. However, there is little rainfall during this time, and crops grown during *Rabi* typically depend either on irrigation or moisture retained in the soil from the *Kharif* rains.

the calendar year before the election is the most salient.[12] This equation will allow us to test, in the Indian context, the general hypothesis of Achen and Bartels (2004) and Healy (2008), that incumbents are punished for "acts of God" in the time leading up to their election.

To control for unobserved geographic heterogeneity, we estimate specifications including state fixed effects or district fixed effects. Our results are robust across specifications and all of our results hold when either state or district fixed effects (or neither) are included. In the following discussion, we focus on the results obtained by using district (and year) fixed effects; this specification controls for the most unobserved variation.

IV. Results

This section reports our main results. We find that abnormally low or high rain in a district leads to lower agricultural output and more disaster relief. On average, severe weather costs the incumbent coalition a large share of the vote, but spending on disaster relief can eliminate some of this cost.

Rainfall matters

We first examine the relationship between severe weather and crop yields, as measured by the log value of agricultural output (in rupees).[13] Table 2 tests various iterations of equation (1), using the natural log of crop yield as the dependent variable. As expected, all specifications indicate a strong relationship between rainfall and agricultural output. The magnitudes are large, and the *t*-statistics with our preferred specifications containing district fixed effects are greater than 4. Standard errors are clustered at the state-year level. Columns (1)-(2) present the linear relationship between normalized rainfall and output: the coefficient is positive and very statistically significant (*t*-statistics

[12] A second option is to include rainfall from previous years directly in the estimating equation; we have done so, and found that the previous year's rain is far more important than earlier years' rainfall, whose impact is often statistically indistinguishable from zero.
[13] Adjusting for inflation is not necessary, as all the regressions include year fixed-effects.

are given in parentheses). On average, a one standard deviation increase in rainfall results in a 3 to 4 percent increase in the value of output.

In columns (3)-(4), we include a quadratic term in normalized rainfall. The linear term is positive, while the quadratic is negative, indicating that revenue increases to an optimal point (the optimum is reached around 0.97-1.62 standard deviations above the mean, depending on the specification, with the result being 1.27 standard deviations for the specification that includes district fixed effects). From this we assume an optimal amount of rainfall of one standard deviation above the mean in our second *weather* measure outlined in Section III.[14]

Columns (5)-(6) measure how the value of output falls as rainfall departs from this optimum. Controlling for district effects and the time trend, the specification in column (6) indicates that rain that is one standard deviation away from this optimum leads to a 5.4 percent drop in agricultural output, on average. Since farmers typically pay a substantial cost to grow crops (seeds, fertilizer, etc.), a 5.4 percent variation in the value of output likely implies a significantly higher amount of variation in a farmer's net income.

It is important to note that adverse effects of this shock to agricultural output are not limited to land-owners. While the effects on price are mitigated to some extent by government price controls, particularly for staples, the demand for agricultural labor is strongly correlated with rainfall: Jayachandran (2006) demonstrates that wage workers suffer significant reductions in wages during adverse weather shocks.

Governments are responsive

We also test for what Besley and Burgess (2002) refer to as government activism: governmental responses to shocks to the population. In the previous section, we predicted that relief expenditures would be higher when crop yields are lower; in other words, when weather is more extreme. Table 3 tests various specifications for equation (2), using the different definitions of *weather* outlined above.

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[14] The optimal amount of rainfall does not vary significantly by state: all states fall within 0.5 to 1.5 standard deviations above the mean.

As Table 3 shows, state disaster relief spending does show the opposite relationship with rain from crop yields. The first two columns indicate that more rain, on average, is associated with less disaster relief. When a squared term for normalized district rainfall is included, we see that extreme amounts of rain lead to higher amounts of disaster spending – particularly droughts. A minimum amount of disaster spending occurs at about one and a half standard deviations of rain above the mean in a district, as estimated in columns (3) and (4), consistent with our estimates of rain and agricultural yield, although the squared term in rain is not significant, suggesting that disaster expenditure particularly increases during droughts. The point estimates in columns (5) through (6) indicate that as rainfall moves one standard deviation further from the optimum, disaster spending goes up by 18-25 percentage points. All of these relationships are statistically significant at standard levels.

Besley and Burgess (2002) present some evidence on what factors affect the general level of government response to droughts. They find that economic factors play little to no role. Urbanization, log state income, budget transfers from the central government, and share of population that is rural do not predict calamity relief expenditures.[15] Budget transfers from the central government for the purpose of calamity relief were often provided as matching funds, directly proportional to the amount spent by the state.[16]

Voters are unimpressed, on average

Poor weather reduces crop yields, which makes voters worse off, but also generates government response, which provides tangible evidence of politicians' desire and ability to help the public. What is the net effect of poor weather on support for the ruling party? In this section, we measure the effect of rainfall shocks on the vote share for the ruling party.

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[15] Their paper does demonstrate an important role of the media in determining the level of government responsiveness. Our results are unaffected by including measures of media distribution (results available upon request).

[16] For a discussion of India's historical calamity relief management, see a speech given on June 25, 2004 by C. S. Rao (http://www.ficci.com/media-room/speeches-presentations/2003/june/june25-natural-rov.htm, last accessed May 24, 2008). We do not include spending by non-governmental organizations in our analysis. Winchester (2000) argues that while NGOs may be efficient providers of disaster relief, only the government has the resources and scale to have meaningful impact on large-scale natural disasters.

We start by graphing the basic relationship between rainfall and voting behavior in India. Figure 1 gives the average vote share of the ruling party by rainfall category: the bar graph gives the mean for each indicated bin; the line gives results from a non-parametric regression. The ruling party does very poorly during extreme droughts, but its performance increases steadily with rainfall, reaching an optimum at a point between 0 and 1 standard deviations above the mean. As rainfall exceeds this optimum, support for the ruling party declines. This relationship mirrors the relationship between rain and crop yields in the previous section.

In Panel B, we present a falsification test, plotting the relationship between current rain and the vote share for the ruling party's vote share in the *previous* election. For example, in Panel A the 1987 West Bengal electoral outcomes is correctly matched to 1986 weather; in Panel B, we instead match 1982 elections to 1986 weather. As expected, there is no effect of rain for this control group, confirming that there is nothing mechanical behind these relationships.

Panel C compares how the ruling coalition's vote share depends on the rain when it is also the incumbent in the constituency, compared to when it is not. In both cases, the same pattern obtains, but the ruling party's vote share is much more sensitive to rainfall when it also controls the constituency. One way to measure this is to calculate how much the party suffers, on average, when rainfall drops from 0-1 standard deviations above the district average to a level more than 2 standard deviations below the district average. Such a drop would penalize the ruling party by 9.8 percentage points if the constituency's parliamentarian was part of the ruling coalition; it would cost the ruling coalition only 2.9 percentage points if it did not control the constituency. When we control for year and district effects, we show that much of this gap disappears. Still, it appears to be the case that the ruling party is hurt more when it also controls the constituency. This evidence suggests that some blame for weather-induced income losses goes to the incumbent parliamentarian in the constituency and not just simply to the ruling coalition.

Table 4 presents regression results estimating the relationship between voting decisions and rainfall. The shape of the relationship between rain and the ruling party's vote share closely resembles the shape of the relationship between rain and crop yields. The coefficient on rain is positive and significant across all specifications; the coefficient on the quadratic term is negative and significant. Likewise, increases in the deviation of rain from the optimal amount causes incumbents to lose vote share. The results in columns (5) and (6) of Table 4 indicate that rainfall one standard deviation from the optimum causes a drop of more than 3 percentage points in the vote that the ruling party receives. The specification in column (6), which includes district fixed effects, gives an estimate that a one standard deviation worsening of the weather will cost the incumbent party 3.25 percentage points of the vote. Given that one-fourth of the contests in our sample are decided by a margin of 5.26 percentage points or less, rainfall is an important determinant of electoral outcomes.

We also test formally the pattern in Panel C of Figure 1, by separately estimating the effect of rainfall on whether this effect is different for incumbents affiliated with the ruling majority versus those who are not. The graphical pattern holds: in our preferred specification, using standard deviations from optimum rain with year and district fixed effects, we find that the ruling coalition suffers a loss of 4.2 percentage points (t = -3.18) when it controls the constituency, compared to a penalty of only 1.8 (t = -1.49) for politicians not affiliated with the incumbent party.[17]

Heterogeneous impact

The effect of rain need not be constant across time or space. An advantage of our setting is the very large number of elections, combined with detailed data at the district level, which allows us to test for heterogeneous effects.

Leigh (2004) shows that voters in more educated countries are less likely to reward their leaders for swings in the global economy beyond their leaders' control. He interprets this as evidence that better informed voters are more rational. In Table 5, we investigate the possibility that different kinds of voter characteristics may predict a higher tendency to respond to the weather. We consider two characteristics: the share of farm households in a district and the literacy rate in a district. Each of these variables comes from the Indian Census, so we only observe data from the years 1971, 1981, and 1991.

[17] If the vote share that the incumbent party receives in a constituency is used as the dependent variable instead of the share of the share for the ruling coalition, generally similar results are obtained. Rainfall has a significant effect on the vote share received by the incumbent party when it is part of the ruling coalition, but it has no significant effect on the vote share it receives when it is not part of the coalition.

We use a district's 1981 literacy rate to proxy for its literacy rate for each election from 1981-1990. For each variable, we include the variable by itself as well as its interaction with the number of standard deviations of rain from the district optimal amount. For the interaction terms, we use the deviation of rainfall from its mean amount in the dataset. Centering the interaction in does not affect the coefficient on the interaction term; it does allow estimation of the coefficient on the linear term at the mean value of rain.

In columns (1) - (2), we present results for share involved in agriculture, columns (3) - (4) adds literacy rate, and (5) - (6) include each of these variables in the same specifications. Somewhat surprisingly, we find no significant effects, although the estimated coefficients have the expected signs. The point estimates suggest that farming districts may punish the incumbent more for weather shocks, and literate districts less.

Do voters reward the government for responding to a crisis?

Even though voters, on average, appear to punish governments for extreme weather beyond their control, we might expect voters to condition their responses on how well politicians respond to extreme weather. A responsive electorate would punish politicians who deal poorly with a weather-caused crisis, but also reward politicians who demonstrate their competence by effectively dealing with a crisis.

To determine how voters' responses to extreme weather are affected by government response to that event, we look at natural disaster relief expenditures made by the government during the year of an election, and interact it with the weather variable.[18]

$$(4) \qquad VoteShare_{dct} = \alpha + \gamma_d + \tau_t + \beta{*}weather_{dt-1} + \lambda{*}relief_{st} + \delta{*}weather_{dt-1}{*}relief_{st} + e_{dt}$$

If voters do respond to the presence of disaster spending in the face of bad weather, then we would expect that δ would be positive in the above regressions.[19] We note that there

[18] We do not lag relief expenditures because they correspond to the fiscal year leading up to the calendar year – thus covering the rainy season under analysis.
[19] Khemani (2004) finds that overall state expenditure does not vary in election years, although the composition of taxes does. We do not find an election year effect on disaster relief spending (p = .77).

is tremendous heterogeneity in government response, and the variance in relief spending increases in the severity of the weather.

Table 6 reports the results of estimating equation (4).[20] We find that voters do indeed reward politicians for disaster spending in response to extreme weather, with δ positive, and consistently significant across all specifications. To understand the magnitude of the coefficient estimate, consider the implied effect that rainfall becoming one standard deviation further from optimal has on disaster expenditure. With state effects, Table 3 indicates that rain becoming one standard deviation further from optimal leads to an increase in log disaster spending of 0.178. Combining this result with the estimate from Table 6, we estimate that a party which responds to bad rainfall with an average increase in disaster spending will gain about 0.52 percentage points of vote share (0.178*2.91) compared to a coalition that does not increase its disaster response when the weather shock occurs. Since a one standard deviation worsening in weather costs the incumbent party 3.25 percentage points of the vote share on average, failing to respond in the face of a crisis should lead to an average cost of 3.77 percent.

Thus an average disaster response offsets about one seventh of the electoral cost of the bad weather. We likewise estimate that a government with a twice-average response would offset about one quarter of the cost of the shock. In other words, the weather still hurts the ruling coalition even when they respond vigorously, but less so. Voters do not filter out entirely the effect of weather, and punish the ruling coalition even for circumstances beyond its control. However, at least some voters do reward responsive governments.

Robustness

Finding that voters are more likely to reelect an incumbent who has responded well to an emergency does not necessarily imply that the voters are directly rewarding the government for its responsiveness during the crisis. A second possibility is that that our measure of government responsiveness (rainfall shock interacted with relief spending)

[20] We note that λ, the coefficient of voting on relief, is negative although small and insignificant – most likely reflecting the electoral effect of non-rainfall catastrophe. This relationship persists with nearly identical coefficients if we include controls for a higher-order polynomial in rainfall.

simply picks up the general competence level of the state government. After all, a government that responds well to one crisis may just be a better government, and therefore do better at the ballot box for a whole host of reasons; crisis management might play only a small part. While this alternative interpretation is consistent with the broader theme of the paper, two pieces of evidence suggest that our narrower, crisis-management interpretation is correct

First, in Appendix 1 we add a number of controls at the state level to our preferred specification in Table 6 that should be correlated with general government competence. None of these variables—state GDP growth, change in cash balances, and budget deficits—is a perfect measure of government behavior; yet, they are likely correlated with voters' perception of the quality of government. As can be seen in the table, the addition of these controls has little impact on the coefficient of rainfall shock interacted with relief spending: it is still statistically and economically quite significant.

Second, we take advantage of non election-year data in an attempt to control for unobservable characteristics of the state government. Our test derives from the well-documented "recency-bias," identified in the psychology literature (Calkins 1896), that individuals put greater weight on more recent events. While general government competence is likely correlated with crisis response, it is unlikely to be correlated with crises only in certain years. On the other hand, voters may be better at recollecting government responses to crises that occurred more recently. Thus, controlling for government responsiveness to crises in "non-recent" years will control for some of the unobserved general government competence that is correlated with crisis response.

In Table A2, we first present strong evidence for the recency bias, by considering separately rainfall the year prior to the election and rainfall in the year before that. Columns (1) and (2) provide strong evidence of this bias: rainfall from more than one year prior to the election does not affect the electorate's decision.

Similarly, we find that, in the earlier year, there is no relationship between vote share for the incumbent coalition and our measure of responsiveness, the interaction between relief expenditure and rainfall (columns (3) and (4)). If our measures were picking up general competence of the government, we might expect the same relationship throughout the electoral cycle, or for the coefficient on responsiveness in the year prior to the election to diminish. Yet we find the coefficient on recent crisis response maintains its magnitude and significance, while on earlier years is economically and statistically insignificant. Taken together, the results from these two tables suggest that endogeneity concerns are not that important in this context.

V. Are Major Crises Different?

Sen's contention that democracies do better at responding to major disasters than to quiet emergencies may stem not from the ability of the opposition to shame the incumbent, as he argues, but rather from the inherent biases of voters. We can investigate whether voters are more sensitive to government responsiveness to major crises than they are to minor crises. As it turns out, the data suggest that extreme rainfall events, relative to less severe events, do present an opportunity for the ruling coalition to gain. Most coalitions do not gain from extreme crises, but the data suggests that particularly good responses may at least not hurt the ruling coalition in this case. We define "bad weather" as rainfall in the 80^{th} to 90^{th} percentiles away from the optimal amount, and "extreme weather" as rainfall in the 90^{th} to 100^{th} percentiles away from the optimal amount. Table 7 measures how governments respond to bad weather and extreme weather. Compared to the omitted category of good weather, bad weather results in a 16-percent increase in relief spending, much smaller than the 57-percent increase during bouts of extreme weather (We report the numbers from column (2), which includes state and year fixed-effects). The coefficients thus suggest that government relief aid increases four times as much during the most severe weather events. The results in columns (3) - (4) attempt to separate these differences into those that occur in election years and those that occur in other years. We observe no significant effects in this decomposition.

The highly non-linear response of government spending to weather would not be surprising if extreme weather was substantially worse for crop yields than bad weather. However, when we regress log crop yield on dummies for bad and extreme weather in columns (1) through (2) of Table 8, we find the impact on agricultural yield is less severe. In the specification with district and year fixed effects, bad weather results in an 8-percent decline in agricultural output, while extreme weather causes a 12-percent drop in output. The declines in yields associated with both bad and extreme weather may well be large enough to create food crises: the Great Bengal Famine of 1943 was associated with a 5-percent reduction in food output (Sen 1981, p. 58), while the Ethiopia famine of 1983-84 involved an 11 percent decline (Drèze 1990). This suggests that a competent government responding optimally to drought is likely to respond not only in cases of severe bad weather, but also in instances of bad weather. However, we observe large responses only in cases of severe weather.

In columns (3) through (4) we explore nonlinear effects of severe weather on voting. Bad weather costs the ruling coalition 4.0 percent of the vote and extreme weather 6.2 percent of the vote, on average, compared to good weather. Ignoring heterogeneity in response, then, we find that voters punish the ruling coalition more for extreme weather than for bad weather – even as the government is more responsive to extreme weather events.

In the bottom panel of Table 8 we examine the relationship between extreme weather, disaster expenditure, and voting behavior. The results are striking. Voters are twice as sensitive to relief spending during extreme weather as they are to relief spending during bad weather. As column (2) indicates, an increase in log relief spending of 1 (for example, by increasing per capita expenditure from Rs. 5 per person to Rs. 13.5 per person) in response to bad weather will lead to an increase of more than 3 percent in the ruling coalition's vote share, while the same increase in response to extreme weather generates a nearly 7-percent increase in vote share. These effects are estimated precisely; the difference between the two effects is statistically significant (p = .032). Although the estimates are statistically precise, we note the limitations of this approach. Since we do not have district-level data on relief, we cannot rule out the possibility that the districts worst hit by the climactic shock are also receiving the most relief. Moreover, since we cannot observe other kinds of "relief"-like visits from politicians, the higher elasticity to measured relief aid under extreme weather may simply be capturing other crisis responses that are, themselves, nonlinear in the severity of the shock.

Given the above caveat, these estimates indicate that a government that reacts with an average response to an extreme weather event will do about 3.8 percent (0.566*6.72) better than a government that fails to increase its response when the drought occurs. Since the average cost to the ruling coalition of an extreme drought is 6.2 percent of the vote, a coalition that fails to respond at all will lose over 10 percent of the vote. A coalition thus can offset about two fifths of the electoral cost of the crisis by responding in an average way. According to this back-of-the-envelope calculation, coalitions whose response is 2.5 times greater than the average response can offset the entire cost of the crisis. But coalitions that respond exactly this same amount (2.5 times the average) during "bad" weather will offset just over one quarter of the electoral cost.[21]

Thus major crises appear to be different. Even though the difference in crop yields between severe and bad weather is of modest size (88 percent versus 92 percent of the average), the voter response to increased government spending is four times larger for severe weather. This result makes sense. Voters punish the ruling coalition for these events beyond a government's control, but respond to government action much more during a severe crisis than a less severe one. Importantly, our results suggest that politicians respond to these electoral incentives.

VI. Conclusion

Using detailed weather, electoral, and relief data from India, we test hypotheses on government responsiveness and electoral outcomes to exogenous events. These literatures have concluded, respectively, that government responsiveness increases in voter sophistication and in the severity of the crisis, and that voters punish incumbent politicians for events beyond their control. Our evidence is consistent with these broad findings. Going beyond these two hypotheses, we ask whether voters reward their leaders for good responsiveness during events beyond their control. We find that voters do reward leaders for correctly responding to climatic events in India, however in general not to a degree sufficient to compensate for the politician's "bad luck" for having presided over a crisis.

[21] The average response to bad weather entails a 3.2*0.164 = 0.52 percent gain in vote share. Thus no response costs the ruling coalition 4.04 + 0.52 = 4.56 percent of the vote. A 2.5 times average response makes up 0.52*2.5 = 1.31 percent of that 4.56 percent.

That said, we also find suggestive evidence that more voters reward leaders for strong responses during major droughts than during less severe weather crises. Together, this provides evidence – as well as an explanation – for Sen's contention that democracies are better at responding to more salient emergencies: voters do a better job of holding governments accountable during these emergencies. Indeed, exceptionally strong responses during major crises may even leave the government stronger than had it not had the misfortune to be at the helm during such an "act of God." Our results suggest, however, that the typical elected policymaker should pray for tranquility rather than turbulence while in office and that even the best governments should fear inconspicuous negative shocks.

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DATA APPENDIX

Elections Data: Elections data are from the Election Commission of India, a quasi-judiciary body set up to administer state and national elections in 1950. Data are available on their website http://www.eci.gov.in/StatisticalReports/ElectionStatistics.asp. For elections not available as electronic datasets, we used Stata programs to convert the pdf files to Stata datasets.

Rainfall: Rainfall data are from Willmott and Matsuura, “Terrestrial Air Temperature and Precipitation: Monthly and Annual Climatologies,” version 3.02, 2001: http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_clim2.html. The database provides rainfall at a .5 degree by .5 degree grid. A degree of latitude is approximately 69 miles.

District Data: We use the database Indian District Data, compiled by Vanneman and Barnes (2000), for information on literacy and urbanization at the district level. The data are available at: http://www.bsos.umd.edu/socy/vanneman/districts/home/citations.html

Agricultural Output: Agricultural output data come from Sanghi, Kumar, and McKinsey (1998), available here: http://chd.ucla.edu/dev_data/datafiles/india_agric_climate.htm. The updated dataset was obtained from Rohini Pande (Harvard University).

Electoral Constituencies: Electoral constituencies were mapped to districts using the 1977 “Delimitation of Parliamentary and Assembly Constituencies Order,” issued by the Election Commission of India.

Data on **coalitions** were obtained for all elections in which a single party did not capture more than 50% of the votes, from contemporary news reports (typically the *Times of India*).

Disaster relief spending data. We use data compiled from state budgets, reported in various issues of the Reserve Bank of India Annual Bulletin. Data prior to 1992 were compiled by Robin Burgess and Stutti Khemani. We obtained data for 1993 onwards from the website of the Reserve Bank of India.

Calamity data are from Robin Burgess, and were the basis of Besley and Burgess (2002). Burgess’ website provides the data from 1951-1996.

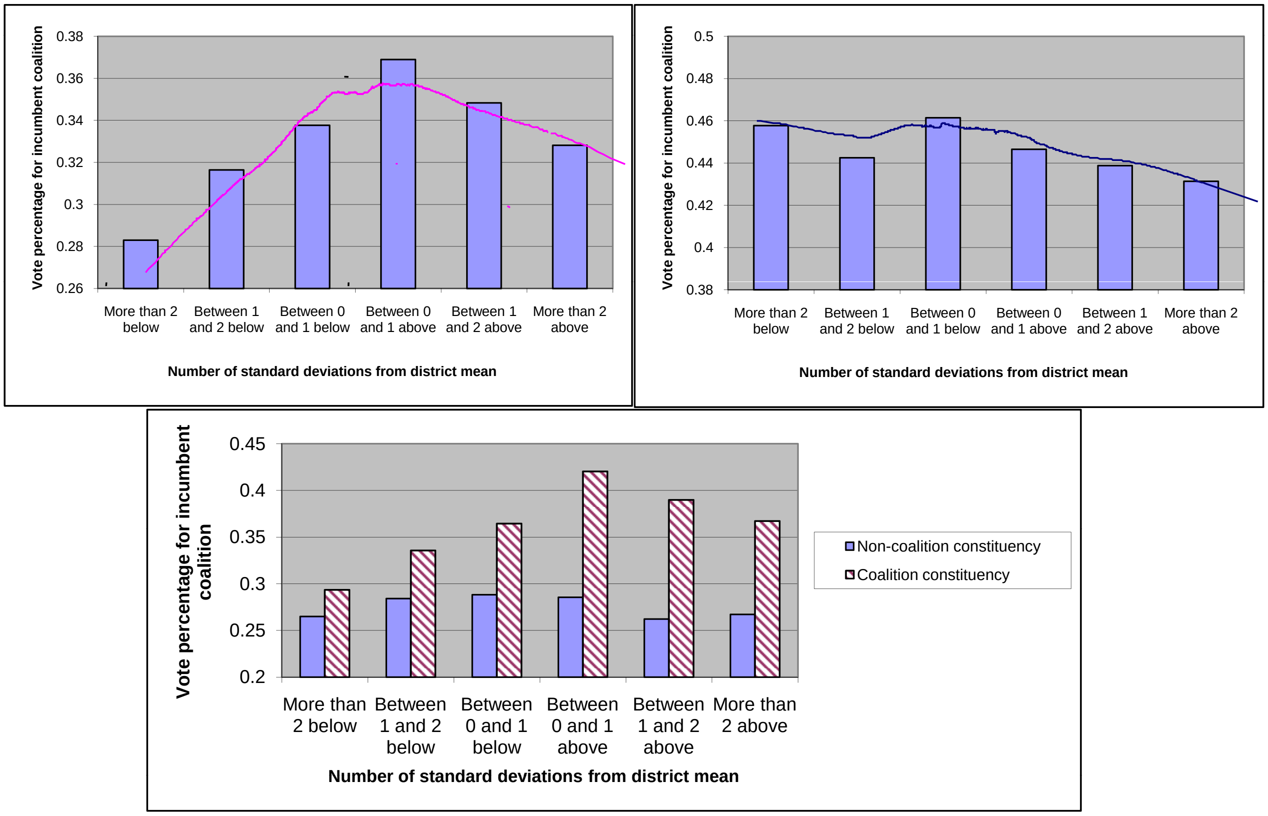

Figure 1: Relating rain to the ruling coalition and incumbent party vote percentage

Panel A (upper left): Coalition vote percentage
Panel B (upper right): Coalition vote percentage in the previous election - falsification test
Panel C (bottom): Coalition vote percentage, broken down according to whether the incumbent party in the constituency is a coalition member

Table 1
Summary statistics

(a) Voting variables

	Mean	S.D.
Number of seats contested in an election	155.9	112.8
Percentage of seats won by top party	56.0	15.6
Vote percentage for winning candidate in a constituency	48.1	11.0
Vote percentage for the ruling coalition	35.3	15.5

(b) Rainfall variables

	Mean	S.D.
Kharif (June - September) rainfall in mm	995	667
Percentage of observations for which rainfall is more than two standard deviations from the optimal amount	18.3%	
Percentage of observations for which rainfall is more than three standard deviations from the optimal amount	1.1%	

(c) Disaster expenditure variable

	Mean	S.D.
Per-capita average expenditure (Rs/person)	10.3	11.8

Table 2
Effect of rain on crop yields (1956-1987)
Dependent variable: Log of total crop value

	(1)	(2)	(3)	(4)	(5)	(6)
Normalized Kharif Rainfall	.0381	.035	.046	.0449		
(Rain from June to September)	(4.41)	(5.85)	(4.76)	(6.62)		
(Normalized Kharif Rainfall)^2			-.0142	-.0177		
			(-2.61)	(-4.69)		
Standard deviations of kharif rain					-.0584	-.0538
from optimal					(-4.95)	(-6.74)
State dummies?	Y	N	Y	N	Y	N
District dummies?	N	Y	N	Y	N	Y
R-squared	.34	.878	.341	.879	.341	.878
N	14108	14108	14108	14108	14108	14108

The rain variables are all standardized by subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. All regressions include year dummies. The major crops are wheat, bajra, maize, rice, and jowar. All of these except wheat are primarily kharif crops.

Table 3

Rain's effect on disaster spending (1960-1999)

Dependent variable: Log of per-capita natural calamity relief expenditure

	(1)	(2)	(3)	(4)	(5)	(6)
Kharif rain	-.1726	-.1289	-.1914	-.1429		
(Rain from June to September)	(-3.04)	(-2.41)	(-3.12)	(-2.47)		
Kharif rain^2			.0681	.0489		
			(1.32)	(1.00)		
Standard deviations of kharif rain					.2458	.1775
from the optimal					(3.00)	(2.28)
State dummies?	Y	N	Y	N	Y	N
Year dummies?	N	Y	N	Y	N	Y
R-squared	.657	.691	.658	.692	.657	.691
N	551	551	551	551	551	551

The rain variables are all standardized by subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state level. Each regression includes a control for total expenditure in the state.

Table 4
Effect of weather on vote for the ruling coalition

Dependent variable: Vote share in the district for the incumbent coalition

	(1)	(2)	(3)	(4)	(5)	(6)
Kharif rain	.0253	.0229	.0291	.0275		
(Rain from June to September)	(2.92)	(2.27)	(3.2)	(2.62)		
Kharif rain^2			-.0073	-.0092		
			(-2.17)	(-2.33)		
Standard deviations of kharif rain					-.0331	-.0325
from optimal					(-3.29)	(-2.77)
State dummies?	Y	N	Y	N	Y	N
District dummies?	N	Y	N	Y	N	Y
R-squared	.355	.452	.359	.458	.355	.454
N	2091	2091	2091	2091	2091	2091

The rain variables are all standardized by subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. All regressions include year dummies. Regressions are weighted by the number of votes in the district.

Table 5
Effect of district characteristics on voter rationality
Dependent variable: Vote share in the district for the ruling coalition

	(1)	(2)	(3)	(4)	(5)	(6)
Standard deviations of rain from optimal	-.0346	-.0328	-.0377	-.0389	-.0377	-.0379
(Rain in June-September year before the election)	(-3.49)	(-2.79)	(-3.27)	(-2.67)	(-3.01)	(-2.43)
District farm share	.0313	-.3045			.0253	-.4291
	(.96)	(-1.6)			(.33)	(-2.19)
District farm share*Standard deviations of rain from optimal	-.0106	-.0367			.0027	-.0084
	(-.42)	(-1.11)			(.06)	(-.14)
District literacy rate			-.0485	.0303	-.0146	-.2106
			(-.67)	(.08)	(-.11)	(-.52)
District literacy rate*Standard deviations of rain from optimal			.0265	.0587	.0297	.0541
			(.53)	(.94)	(.36)	(.56)
State dummies?	Y	N	Y	N	Y	N
District dummies?	N	Y	N	Y	N	Y
R-squared	.36	.46	.356	.456	.356	.459
N	2063	2063	2026	2026	2026	2026

The rain variables are all standardized subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. All regressions include year dummies. Regressions are weighted by the number of votes in the district.

Table 6
Weather, voting, and relief expenditure

Dependent variable: Vote share in the district for the ruling coalition

	(1)	(2)
Standard deviations of kharif rain from optimal last year	-.0386	-.036
	(-4.08)	(-3.28)
ln (relief expenditure last year)	.0063	.0077
	(.35)	(.38)
ln (relief expenditure last year) * standard deviations from optimal last year	.0222	.0291
	(2.35)	(3.3)
State dummies?	Y	N
District dummies?	N	Y
R-squared	.387	.503
N	1756	1756

The rain variables are all standardized subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. All regressions include year dummies. Regressions are weighted by the number of votes in the district.

Table 7
Rain's effect on disaster spending in crises (1960-1999)

Dependent variable: Log of per-capita natural calamity relief expenditure

	(1)	(2)	(3)	(4)
Bad weather dummy	.2701	.1641	.3417	.2106
	(1.9)	(1.23)	(2.13)	(1.39)
Extreme weather dummy	.6523	.5663	.5172	.4195
	(2.44)	(2.25)	(1.6)	(1.36)
Election year			.0691	.0397
			(.43)	(.26)
Election year*bad weather dummy			-.3114	-.1978
			(-.93)	(-.62)
Election year*extreme weather dummy			.5268	.573
			(.98)	(1.18)
State dummies?	Y	N	Y	N
R-squared	.659	.693	.661	.694
N	551	551	551	551

The rain variables are all standardized by subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. All regressions include year dummies. Each regression includes a control for total expenditure in the state.

Table 8

Extreme weather, yields, voting and relief expenditure

(a) Dependent variable:

	Log of crop yield		Vote share for the ruling	
	(1)	(2)	(3)	(4)
Bad weather dummy	-.0473	-.0785	-.0338	-.0404
	(-2.26)	(-6.47)	(-2.04)	(-2.01)
Extreme weather dummy	-.1068	-.1265	-.0522	-.0618
	(-3.44)	(-5.59)	(-2.86)	(-2.85)
State dummies?	Y	N	Y	N
District dummies?	N	Y	N	Y
R-squared	.340	.878	.344	.45
N	14108	14108	2091	2091

(b) Dependent variable: Vote share in the constituency for the ruling coalition

	(1)	(2)
ln (relief expenditure last year)	.0001	-.0004
	(0)	(-.02)
Bad weather dummy	-.0389	-.0438
	(-2.25)	(-2.29)
ln (relief expenditure last year) * bad weather dummy	.0297	.032
	(1.94)	(1.90)
Extreme weather dummy	-.0578	-.0648
	(-3.26)	(-3.24)
ln (relief expenditure last year) * extreme weather dummy	.0644	.0672
	(3.30)	(3.30)
p -value for test of equality between the coefficients for the two interaction terms	.018	.032
State dummies?	Y	N
District dummies?	N	Y
R-squared	.377	.496
N	1756	1756

The rain variables are all standardized by subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. Each regression in Panel B includes a control for total expenditure in the state. All regressions include year dummies. Regressions are weighted by the number of votes in the district.

Table A1
Weather, voting, and relief expenditure (controlling for good government)

Dependent variable: Vote share in the district for the ruling coalition

	(1)	(2)	(3)	(4)
Standard deviations of kharif rain from optimal last year	-.0296 (-2.84)	-.0267 (-2.34)	-.0282 (-2.64)	-.0246 (-2.12)
ln (relief expenditure last year)	.007 (.36)	.0102 (.48)	.0054 (.29)	.0061 (.29)
ln (relief expenditure last year) * standard deviations from optimal last year	.0249 (2.85)	.0268 (2.42)	.0203 (1.7)	.0276 (2.65)
State GDP growth in the previous year	.3003 (1.28)	.3024 (1.25)	.3507 (1.63)	.3669 (1.51)
Change in cash balances (in thousands)		-.0015 (-.7)	-.0014 (-.74)	-.0011 (-.53)
Budget deficit (in thousands)			.0016 (1.76)	.0016 (1.52)
Population growth				-2.699 (-.29)
State dummies?	N	N	N	N
District dummies?	Y	Y	Y	Y
R-squared	.512	.496	.396	.507
N	1756	1605	1605	1605

The rain variables are all standardized subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. All regressions include year dummies. Regressions are weighted by the number of votes in the district.

Table A2
Weather, voting, and relief expenditure

Dependent variable: Vote share in the district for the ruling coalition

	(1)	(2)	(3)	(4)	(5)	(6)
Standard deviations of kharif rain from optimal last year	-.0325 (-2.78)	-.031 (-2.66)	-.0383 (-4.2)	-.0356 (-3.39)	-.0297 (-3.19)	-.0268 (-2.52)
ln (relief expenditure last year)			.0139 (.71)	.0149 (.69)	.0168 (.86)	.0182 (.85)
ln (relief expenditure last year) * standard deviations from optimal last year			.0229 (2.45)	.0295 (3.45)	.0247 (2.94)	.0314 (4.09)
Standard deviations of kharif rain from optimal two years previous	.0101 (1.05)	.0128 (1.4)	.0084 (.92)	.0059 (.62)	.0117 (1.25)	.0097 (1.03)
ln (relief expenditure two years previous)			-.0061 (-.31)	-.008 (-.38)	-.0065 (-.36)	-.0076 (-.39)
ln (relief expenditure two years previous) * standard deviations from optimal two years previous			-.0091 (-1.19)	-.0075 (-.99)	-.0051 (-.65)	-.0037 (-.48)
State dummies?	N	N	Y	N	Y	N
District dummies?	Y	Y	N	Y	N	N
R-squared	.456	.458	.393	.508	.415	.527
N	2091	2091	1756	1756	1756	1756

The rain variables are all standardized subtracting the district mean and dividing by the district standard deviation. t-statistics are in parentheses. Standard errors are corrected for clustering at the state*year level. All regressions include year dummies. Regressions are weighted by the number of votes in the district.