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## Repository Citation

Cole, Shawn; Healy, Andrew; and Werker, Eric, "Do Voters Demand Responsive Governments? Evidence from Indian Disaster Relief" (2012). *Economics Faculty Works*. 24.  
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## Recommended Citation

Cole, Shawn, Andrew Healy, and Eric Werker. 2012. "Do Voters Demand Responsive Governments? Evidence from Indian Disaster Relief," *Journal of Development Economics* 97(2): 167-181.

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# Do Voters Demand Responsive Governments? Evidence from Indian Disaster Relief\*

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October 5, 2010

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## I. Introduction

A key feature of democracy is the accountability provided by voters, who choose whether to re-elect a politician or party based on demonstrated performance. Recent evidence suggests, however, that voters may punish politicians even for events outside their control. For example, Achen and Bartels (2004) find that leaders are punished for droughts, floods, and even shark attacks that occur under their watch. In a similar vein, Wolfers (2006) and Leigh (2009) show that incumbent politicians are rewarded or punished for movements in the economy outside their plausible sphere of influence. This behavior violates most basic models of democratic accountability and has been advanced as evidence of voter irrationality. An inability to correctly distinguish political competence from exogenous shocks outside the control of a politician would imply weaker democratic accountability, and may reduce governmental incentives to pursue welfare-maximizing policies.

On the other hand, a bad shock does not necessarily imply political disaster for incumbent politicians. In India, for example, the Bharatiya Janata Party (BJP) leader Jagdish Shettigar remarked that “a bad monsoon per se will not affect electoral fortunes, but its management definitely will.” A food shortage tested the “administrative skills” of the government. Shettigar noted that the BJP lost a round of elections in Delhi in 1998, in the so-called “onion crisis,” not because of the severe drought, but because the government was perceived to have handled the crisis poorly.<sup>1</sup>

This example suggests an omitted analysis from recent papers that have attempted to demonstrate failures in electoral accountability by showing that voters respond to random events: the government’s response to the external shock. After all, governments can take action to mitigate the effects of droughts, assist flood victims, and respond to external shocks to the economy to the benefit of local consumers and business. Indeed, it is entirely possible that voters are able to infer *more* about government competence by observing state response to a crisis than they can from other indicators like movements in the business cycle or the budget deficit, which are plagued with multiple inference challenges (Drazen, 2000). In the context of the United States, Healy and Malhotra

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<sup>1</sup> “How Ballot Hopes Rest on Good Monsoon,” Financial Express, April 21, 2003.

(2009) demonstrate that voters respond to natural disaster relief efforts, although the implied electoral incentives for elected officials appear to still fall well short of public welfare maximization.

In this paper, we use weather crises in India to examine the hypothesis that voters respond to events beyond a government's control; our framework explicitly incorporates the fact that voters also evaluate the government's response to exogenous events. Specifically, we look at the decisions that Indian voters make in state elections, using the quality of the monsoon rains as an exogenous shock to welfare. 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. The overwhelming majority of the population is involved in agriculture, and the quality of seasonal rains, are incredibly important to household welfare. Rainfall shocks, clearly beyond the control of politicians, are measured accurately over a long time series. Moreover, the Indian government statistics on state-level disaster relief expenditures are of unusually high quality for a developing country. This enables precise estimation, as well as the flexibility to explore heterogeneous treatment effects and non-linear relationships.

In addition, we build on the small body of work beginning with Sen (1981) that explores governmental response to weather crises in India. Besley and Burgess (2002) show that state governments in India are responsive to agricultural and weather-induced catastrophes, but that 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. Building on this research, we analyze the government response in a framework that acknowledges the potential for voter irrationality. Our paper seeks to make three contributions to the existing literature: we examine whether voters reward governments for responsiveness during weather crises; we identify specific behavioral biases, including the attribution bias and the recency bias that an electorate seems to collectively display; and we examine whether governments respond strategically to voter behavior.

Our paper first establishes that rainfall is an important determinant of agricultural output, a result that is not surprising given the low level of irrigation across most of our sample. We then confirm, in the Indian context, the basic findings of Achen and Bartels (2004) that elected officials fare worse when natural disaster strikes. We show that, on average, incumbent parties that run for re-election get punished for bad weather, losing more than three percent of the vote for each standard deviation that district-level rainfall deviates from its optimum level. This effect is driven almost entirely by the response of voters to the ruling coalition, as incumbents are only significantly punished when they are part of that coalition.

We then attempt to test the “Shettigar” theory, allowing the voters to condition their response on the government’s management of the crisis. The analysis is motivated by a reduced-form framework that treats the government’s response to an exogenous shock as a useful and potentially less-noisy piece of information with which voters can evaluate the competence of the government. Several hypotheses motivated by the framework are tested.

We confirm that governments do increase the level of disaster relief to areas hit by rainfall shocks. 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.

Finally, we investigate voter and politician behavior with respect to a simple behavioral bias, the propensity for voters to respond only to those events and outcomes that occur soon before an election (e.g., Fair 1978). Since governments are in power for several years, we compare the electoral response of voters to rainfall shocks in various years of the election cycle. As it turns out, voters only reward governments for their relief in the season leading up to the election. This result poses a challenge to our reduced-form framework that suggests governments can only gain through vigorous response. We explore the consequences of a strategic government response to rainfall shocks, and test

for such behavior around election timing. The results indicate that governments respond to the voter recency bias by delivering more crisis relief during election years.

The rest of the paper is organized as follows. Section II constructs a formal model in which voters respond to governmental relief efforts at the polls. Section III summarizes the context of the political system in India and related research, while Section IV describes our data set and empirical specifications. Using the Indian data, Section V replicates and extends the tests of previous papers, analyzing the effect of rainfall on crop yields and voting outcomes. It then tests how governments respond to crises, and how voters evaluate their responses. Section VI tests specifically for a particular behavioral bias among Indian voters, recency bias, and examines whether governments strategically respond to this bias. Section VII concludes.

## **II. Modeling Voters**

To clarify what may be learned from voter behavior following rainfall shocks, we lay out a simple two-period model, in which voters use observable information to form an opinion of the politicians unobservable competence. Our model is similar to the career concerns model in Persson and Tabellini (1998) and the models in Rogoff and Sibert (1988) and Rogoff (1990), but simpler insofar as we consider an environment without strategic action.

We focus on voters' desires to evaluate an official's performance based on the information available to them at the time. Our model makes two important predictions: first, contrary to what is often casually stated in the literature, voters may rationally "punish" politicians for bad weather, if they cannot perfectly identify the extent to which the weather shock is responsible for income losses or gains. Second, the model predicts, under certain information structures, that all politicians may be hurt by adverse weather, but higher-quality governments may be hurt less, as they signal their type through the quality of their response to a crisis.

We start by outlining a textbook example. Consider an initially homogenous voting population, who earns income  $y$ , which is a function of the ability of the politician,  $\theta$ , a random weather shock,  $v$ , and an idiosyncratic shock  $\varepsilon$ :

$$y = \theta + v + \varepsilon \tag{1}$$

Voters seek to reelect a politician if she is of sufficiently high quality, otherwise they prefer to vote against the incumbent and replace her with a new politician, who we assume is also drawn from an (independent) uniform  $[0,1]$  distribution.<sup>2</sup> We assume that the rainfall shock is a negative shock to income that is distributed uniformly on  $[-1,0]$ . Finally, we also assume that the idiosyncratic shock is drawn from a uniform  $[0,1]$  distribution.

If the weather shock is perfectly observed,  $E[\theta|y,v]=(y-v)/2$ . This relationship is depicted in Panel A of Figure 1. This relationship yields the following result:

**Result 1:** If income is additive in ability, the rainfall shock, and an idiosyncratic shock, and weather is perfectly observable, then  $\frac{\partial E[\theta|y,v]}{\partial v} = 0$ . For a politician of a fixed ability, the probability of re-election is invariant to the quality of rainfall.

In contrast, voters may either not perfectly observe the rain or, more plausibly, be imperfectly informed about the extent to which the rainfall shock affects income. If we assume instead that the weather shock is unobservable, then  $E[\theta|y]=1/3+y/3$ . The relationship is depicted in Panel B of Figure 1.

**Result 2:** If income is additive in ability, the rainfall shock, and an idiosyncratic shock, and weather is unobservable, then  $\frac{\partial E[\theta|y]}{\partial v} > 0$ . For a politician of a fixed ability, the probability of re-election increases with the quality of the weather.

Note that an intermediate case, in which shocks are imperfectly observed, will yield the same prediction as in Result 2: since the shock is not perfectly observed, voters rationally downgrade their expectation of the politician's competence when observed income is lower.

Of course, government intervention may be able to ameliorate some of the negative effect of a rainfall shock: for example, through disaster relief spending, distribution of emergency food grains, or other measures. We now consider the

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<sup>2</sup> The standard for re-election is typically posited to be .5, the mean of the distribution of politician quality, though this need not be the case, if, for example, ideological considerations also matter. If voters have an ideological preference for the incumbent party, for example, they may decline to reelect a politician only if her expected ability is less than .4. The exact cutoff is not important for the results we derive; we only need the probability of reelection to be weakly increasing in expected ability.

implications of a somewhat richer model, in which the politician's ability plays an important role in determining the impact of rainfall shocks on income.

In particular, we continue to assume that weather is unobserved and that the income process is as follows:

$$y = \theta + (1-\theta)*v + \varepsilon \quad (2)$$

In this case, the highest ability politician is able to completely neutralize the effect of a rainfall shock, while the worst quality politician is entirely ineffective in mitigating a shock. We again consider the case when weather is observable, and the case when it is not. We maintain the assumption that  $\theta$  and  $\varepsilon$  are uniformly distributed on the interval  $(0,1)$  and that  $v$  is distributed on the interval  $(-1,0)$ , meaning the range of possible income is again  $-1$  to  $2$ .

If the weather shock is not observed, then  $E[\theta|y]$  is again an increasing function in income. Panel C of Figure 1 graphs this relationship:

As in Case 1, politicians are hurt because voters cannot fully determine whether income is low because the politician has low skill or because of a weather shock.

**Result 3:** If income is described as in equation (2), and voters do not observe rainfall shocks, then the probability of election increases with the quality of the weather.

In addition, the model – as would any related model where weather is imperfectly observed as opposed to unobserved – predicts that high-quality incumbents would be hurt less by bad weather than low-quality incumbents. High-quality incumbents are better able to offset the consequences of the negative shock, and therefore the shock to income is less for these incumbents.

Panel D of Figure 1 shows how the expectation of incumbent quality varies as a function of rainfall. The lines are steeper for lower-quality incumbents since their low quality is particularly revealed by their inability to stop the consequences of low rainfall. On the other hand, high-quality incumbents are still hurt by the negative shock to income, but the effect on expected competence is much smaller since they ameliorate much of the negative shock.

**Result 4:** If politicians can mitigate rainfall shocks, as described in equation (2), and weather is unobservable, negative rainfall shocks hurt all politicians' reelection chances, where  $\theta < 1$ . This effect is more pronounced for less effective politicians.



This result corresponds closely to our empirical results, where we find that incumbent politicians who respond vigorously with relief are hurt significantly less by negative rainfall shocks than politicians – of low competence in the context of the model – who respond less strongly.

Finally, we consider the possibility that voters are “irrational,” in the sense that they believe that the data generating process is different from the true data generating process. To illustrate, suppose voters believe that income is generated in the following manner:

$$y = -1 + 2 * \theta + \varepsilon \quad (3)$$

Including the constant -1 ensures that the range of possible incomes matches previous examples. This model might be explained by the well-documented “attribution bias,” in which individuals seek to attribute outcomes to actors who are identified, even if the actor in a situation has no control over the situation (Ross, 1977). In this simple irrational model, voters do not believe that weather affects income, hence whether weather is observed does not matter.

Voters’ inference in this case is graphed in panel E of Figure 1.

$$E[\theta|y] \begin{cases} 100 + \frac{y}{4} & y \leq 0 \\ \frac{1}{4} + \frac{y}{2} & 0 \leq y \leq 100 \\ \frac{3}{4} + \frac{y}{4} & 100 \leq y \end{cases}$$

What is immediately clear from the model is that the reduced form relationship between rainfall and voter behavior is quite similar to Result 2 and Result 3: voters punish politicians for poor rainfall.

Taken together, these results suggest that it may be difficult to distinguish between several plausible theories of voter behavior based on the observed relationship between rainfall and electoral performance. A finding of no relationship between rainfall and reelection prospects would support the model in which voters observe rainfall and unobservable ability does not interact with weather shocks. However, a broad range of alternative models yields the prediction that voters punish politicians for bad weather, and that this punishment may be rational or irrational. We thus focus on documenting the empirical relationships between weather, economic performance, and electoral support.

Our aim is not simply to determine whether voters respond to weather, but to use the richness of the data to describe nuances and features of this relationship that inform our understanding of political economy in emerging markets.

### **III. 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 work most closely related to the present paper 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. Afzal 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 isolate one particular mechanism that can plausibly explain voter behavior, but rather to better understand the incentives faced by electoral officials and how politicians react to these incentives.

#### ***Political Context***

In this paper we focus on state-level elections. State governments in India are responsible for most public goods in India, including agricultural infrastructure, health, education, and disaster relief. Our main measure of state responsiveness is state spending on disaster relief.

While we are unable to obtain detailed data on how disaster relief is spent, Rathore (2005) conducts an analysis of disaster relief in Rajasthan, a state that may be fairly representative of India, over the period 1999-2005. He finds the primary relief expenditures are on food aid, drinking water, fodder supply, and temporary employment schemes.

India has a federal system of government, with a bicameral national legislature, but typically unicameral state legislatures.<sup>3</sup> 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.

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 but, as in other parliamentary systems, may be called earlier.<sup>4</sup>

Direct election campaign expenditure is relatively restricted in India, as compared to the United States. 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, 2009, for examples). In Russia, such manipulations have been shown to aid re-election (Akhmedov and Zhuravskaya, 2004).

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<sup>3</sup> A few states have upper houses, with indirect elections; for those states, we study the more important chamber, the popularly elected lower house.

<sup>4</sup> 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." In practice, most of the instances of Governor's rule follow a collapse of the ruling coalition (National Commission to Review the Working of the Constitution, 2002).

### *Politics and parties*

The Indian National Congress Party, which led the independence movement, initially dominated Indian politics, ruling the federal parliament and most state assemblies following independence. After 1977, stronger opposition parties emerged, and Congress victories were no longer assured.

Because, as noted by Chhiber and Kollman (1998), in any given electoral district there are usually two effective parties, we simplify analysis of state coalitions by coding parties that are part of the ruling coalition as “majority,” with all others serving as “opponents.”

### **IV. 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. We augment this dataset with information about rainfall, crop yields, population characteristics, and disaster relief spending.

Electoral data are from the Election Commission of India. Unless otherwise noted, we aggregate voting outcomes up from the constituency level to the district level.<sup>5</sup> 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, the period after which Congress victory was no longer assured.

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.<sup>6</sup> 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

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<sup>5</sup> We do this to ensure our standard errors are conservative—we observe rainfall variation only at the district level.

<sup>6</sup> 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.

agricultural crops in India. The dataset runs from 1950 to 1994; for the subsequent years, we use an updated version created by Rohini Pande.<sup>7</sup>

Combining these datasets, we conduct all analysis, unless otherwise noted, at the district-election level.<sup>8</sup> The unit of observation is, unless otherwise noted, the administrative district-election interaction. Finally, we note that disaster relief spending data are only available at the state level (for each year). 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. The median value of the standard deviation of rainfall within-district over our sample period is 609 mm, while the 25<sup>th</sup> percentile is 639 and the 75<sup>th</sup> percentile 1176.

Panel B also reports the share of variation in rainfall explained by year and district fixed-effects. While geography, unsurprisingly, explains substantial amount of variation in rainfall, it is worth noting that year fixed-effects alone explain only a tiny fraction of rainfall variation. The monsoon is not a uniform event; rather, there is substantial variation even within a year.

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

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<sup>7</sup> 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.

<sup>8</sup> While the electoral data are available at the constituency level, we aggregate constituency outcomes to the district level to match the granularity of our other data sources. The original unit of observation for our analysis was the electoral constituency, rather than the administrative district, and our results are unchanged if we estimate at that level.

monsoon period.<sup>9</sup> 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  $\overline{Rain}_d$  and  $s_d$  are the mean and 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.<sup>10</sup>

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.<sup>11</sup> 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, voting, and government response. The primary contribution of this paper is the elucidation of the relationship between weather, government, and voters. Of course, it is necessary first to verify that weather indeed affects crop yields.

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

$$Yield_{dt} = \alpha + \gamma_d + \tau_t + \beta * Weather_{dt} + e_{dt} \quad (4)$$

where  $Yield_{dt}$  is a measure of the log value of a district's crop output, and include fixed effects for district,  $\gamma_d$ , and year,  $\tau_t$ . We weight the regressions by the number of votes in

<sup>9</sup> 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.

<sup>10</sup> 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.

<sup>11</sup> These measures are very similar to the "Standardized Precipitation Index," developed in McKee, Doesken, and Kleist (1993), and are consistent with agro-climatic models from test plots which tend to measure a linear relationship between rainfall and crop yield (See Allen et al. (1998), or Cole (2007) for an accessible discussion). As a robustness test (available from the author), we substitute the Standardized Precipitation Index for each district in each year, and find nearly identical results.

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 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.

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

$$VoteShare_{dct} = \alpha + \gamma_d + \tau_t + \beta * weather_{dt-1} + e_{dt} \quad (5)$$

$VoteShare_{dct}$  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 the calendar year before the election is the most salient.<sup>12</sup> This equation will allow us to test, in the Indian context, the general hypothesis of Achen and Bartels (2004) and Healy (2009), 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.

## V. Are Indian Politicians Punished for Poor Rainfall?

If American voters punish incumbents for such “acts of God” as shark attacks and droughts, then we might expect Indian voters might do the same for poor rains. This section repeats the basic Achen and Bartels tests in our Indian context. We find that abnormally low or high rain in a district leads to lower agricultural output. On average,

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<sup>12</sup> We will study the role of rainfall in two or more seasons before the election below.

severe weather costs the incumbent coalition a large share of the vote. Voters only punish their representative with fewer votes if they are from the same party as the ruling coalition in the state.

### ***Rainfall matters for yields***

We first examine the relationship between severe weather and crop yields, as measured by the log value of agricultural output (in rupees).<sup>13</sup> Table 2 tests variations of equation (4), using the natural log of the total value of crop yield as the dependent variable.<sup>14</sup> As expected, all specifications indicate a strong relationship between rainfall and agricultural output. The magnitudes are large, and statistically significant; our preferred specification, which contains district fixed effects, yields a *t*-statistic above 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 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 IV.<sup>15</sup>

Columns (5)-(6) measure how the value of output falls as rainfall departs from this optimum. Controlling for district effects and time effects, 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

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<sup>13</sup> Adjusting for inflation is not necessary, as all the regressions include year fixed-effects.

<sup>14</sup> We use the sum of the value of the 25 most common crops, as reported in the Willmott and Matsuura data.

<sup>15</sup> 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.



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.

### ***Voters punish the ruling coalition for adverse rainfall***

Poor weather reduces crop yields, which makes voters worse off, but also generates government response, providing 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.

We start by graphing the basic relationship between rainfall and voting behavior in India. Panel A of Figure 2 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 deviation 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 of Figure 2, 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.

Table 3 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 3 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. Voters appear to suffer an attribution bias, linking their rain-induced economic hardship to government behavior.

In the balance of this section, we examine which politicians are punished, and whether various groups of voters behave differently.

### ***Targeted disappointment***

There are two ways voters might express displeasure against politicians: simply by voting against their incumbent politician, no matter what her or his party is; or by voting against the state ruling coalition. Voters seeking a change in government would presumably vote in this latter fashion.

Figure 3 graphs the ruling coalition's vote share as a function of rainfall, for cases when the ruling party is also incumbent in the constituency (striped bar), and when the opposition is the incumbent party in the constituency (solid bar). 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. We test this formally in Table 4. We begin by replicating our analysis at the constituency (rather than district) level, separately estimating the effect of rainfall and relief spending on the electoral fortunes of the state ruling party or coalition. Consistent with the district level results, we find a large, negative effect: a one standard deviation shortfall in rain results in 3.8 percent fewer votes for the incumbent coalition.

Splitting the sample into constituencies represented by the ruling coalition (columns (3) and (4)), and those in which an opposition member is an incumbent

(columns (5) and (6)), we find striking evidence in favor of the view that voters seek a change in government. Incumbents who are affiliated with the ruling coalition suffer an average 2.23 percentage-point loss of the vote following a one standard deviation rainfall shortfall, while incumbents who are not in the ruling coalition benefit from adverse rainfall, *gaining* an average of about 2 percentage points of the vote for each standard deviation by which rainfall deviates from the optimum.

As a final check, we further break down the analysis to analyze separately constituencies in which the incumbent party is the leader of the ruling coalition and those in which the incumbent party is a member, but not the lead party, of the ruling coalition. We find negative and significant results for both of these subgroups (not reported), neither of which is statistically distinguishable from the point estimates reported in columns (3) and (4).

These results are quite striking when seen in the context of dominant perceptions of patronage politics in developing countries. Observers of developing-country politics, particularly in less mature democracies than India's, argue that weak parties limit the ability of the state to move beyond clientelistic behavior (e.g. van de Walle, 2003). Roninger (2004) describes the clientelist view:

Those in control – the so-called patrons, sub-patrons and brokers – provide selective access to goods and opportunities and place themselves or their supporters in positions from which they can divert resources and services in their favour. Their partners – the so-called clients – are expected to return their benefactors' help, politically and otherwise, by working for the patron at election times or boosting the patron's prestige and reputation.

In the narrowest sense, this trading of political favors for votes occurs at the level at which the votes are delivered: the constituency. Yet the behavior exhibited by Indian voters to reward or punish the political party goes beyond this narrow view.

By correctly (though not necessarily rationally) identifying the ruling party as the one worth blaming, rather than individual candidates representing their constituency, the Indian voters indicate that patronage politics are not just local. While the Congress Party is well known for its patronage tactics (Weiner, 1967), these results point towards what Weingrod referred to as “political-party directed patronage,” which, he argues, is indicative of greater state power and a development-oriented polity (1968).

In our data, not only are incumbents affiliated with the dominant party punished for bad rain, but those who are not affiliated gain votes by almost an equal amount. This gain is driven by the fact that elections are a zero-sum game, and one candidate's loss is another candidate's gain. Thus while we observe party- rather than politician-linked patterns of patronage, that several percentage points of the electorate can change allegiance after an adverse shock indicates that patronage politics—should they be reaching those swing voters—are driven not just by output, but by outcomes.

### *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 (2009) 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. 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 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.

In sum, the Indian data are consistent with U.S. and global data from different shocks: they describe an electorate that seems to punish incumbent politicians for acts beyond their control. We add to the existing literature by showing that not all incumbent politicians, but only those aligned with the ruling coalition, are punished. In the following section, we consider the possibility that response to crises might provide useful information to voters.

## VI. Are Governments Rewarded for Responding to Disasters?

### *Governments are responsive*

Our measurement of the relationship between rainfall and relief is similar to that for crop yield or voting in the previous section. As noted earlier, since district-level relief spending is not available, we use state-level data. The mean level of relief spending per capita was 10.3 rupees (approximately \$0.32 today), with a standard deviation of 11.8. 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.

$$Relief_{st} = \alpha + \gamma_s + \tau_t + \eta * TotalSpending_{st} + \beta * \overline{Weather}_{st-1} + e_{st} \quad (6)$$

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 (4): more extreme weather should generate higher relief spending.<sup>16</sup> Table 6 tests various specifications for equation (6), using the different definitions of *weather* outlined in Section IV.

<sup>16</sup> 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.

As Table 6 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. 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.

***Do voters reward the government for responding to a crisis?***

To determine how voters’ responses to extreme weather are affected by government response to that event, we look at natural disaster relief expenditure made by the government during the year of an election and interact it with the weather variable.<sup>17</sup>

$$VoteShare_{dct} = \alpha + \gamma_d + \tau_t + \beta * weather_{dt-1} + \lambda * relief_{st} + \delta * weather_{dt-1} * relief_{st} + e_{dt} \quad (7)$$

If voters do respond to the presence of disaster spending in the face of bad weather, then we would expect that  $\delta$  would be positive in the above regressions.<sup>18</sup>

We note several caveats with these regressions. First, as mentioned, we observe relief spending only at the constituency level. Second, because we are unable to identify plausibly exogenous variation in government spending that is uncorrelated with rainfall, it is possible that the regression suffers from omitted variables bias: if more competent governments administer aid more effectively and also deliver more of it, we are unable to determine what fraction of the electoral boost from aid administration is due to general competence as opposed to aid delivery. Similarly, voters may demand things from the

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<sup>17</sup> 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.

<sup>18</sup> Khemani (2004) finds that overall state expenditure does not vary in election years, although the composition of taxes does.

government other than traditional relief, such as price subsidies or high-profile visits. These alternative palliative measures may be correlated with our measure of relief.

The first two columns of Table 7 report the results of estimating equation (7). We find that voters do indeed seem to reward politicians for disaster spending in response to extreme weather, with  $\delta$  positive and consistently significant across all specifications. In the third and fourth column we perform the same analysis at the state level. Since it is limited to election years, the number of observations falls to 79, but even with that small sample the  $\delta$  is positive, of a similar magnitude as with the district-level regressions, and marginally statistically significant ( $t$ -statistic of 1.74).

Of course, it is also possible that forward-looking incumbent parties strategically reallocate electoral (and patronage) spending in response to rainfall shocks, thereby mitigating the effect on their ability to form a ruling coalition. Columns (5) and (6) of Table 7 investigate this possibility. We estimate equation (7), but put "ruling coalition seat share" on the left hand side. The point estimates are large: -0.13 and -0.22, depending on whether we include state fixed effects, though only the latter estimate is statistically significant at the ten percent level, as the sample size is substantially smaller (79 observations). These large point estimates, though, are consistent with the fact that many elections in India are quite competitive: five percent of elections in our sample are decided by a margin of less than 1 percentage point of votes, while 25 percent are decided by a margin of five percentage points or less. These results suggest that state governments are not very effective in coordinating resources to eliminate the effect of voter discontent.

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 6 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 column (2) of Table 7, we estimate that a party which responds to bad rainfall with an average increase in disaster spending (noting that the endogeneity concerns make this calculation less precise) will gain about 0.52 percentage points of vote share ( $0.178 \times 2.91$ ) 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 3.75 (column (2) of Table 4) percentage points of the vote share on average, failing to respond in the face of a crisis should lead to an average reduction of votes of 4.25 percent.

It should be stressed that these calculations examine local (district-level) response to state-wide disaster relief expenditures: more localized relief expenditure data are not available. We cannot, for example, observe the efficiency with which relief expenditures are disbursed. A government allocating relief to the hardest-hit areas may well receive a more favorable response from voters than a government seen as allocating relief to politically connected areas. Nevertheless, our sample includes a very diverse set of states, over quite a long period of time, and the point estimates we describe may be seen as average effects.

Thus, the average disaster response, if correctly measured, offsets about one-seventh of the electoral cost of the bad weather. Similarly, a government with a twice-average response would offset about one-quarter of the cost of a rainfall shock. In other words, the weather still hurts the ruling coalition even when they respond vigorously, but less so. Voters do not filter out the entire effect of weather, but rather punish the ruling coalition for circumstances beyond its control. However, at least some voters do reward responsive governments, even if the electorate as a whole punishes them more for the negative events than it rewards them for the robust response.

These results are related to the literature on political business cycles, which has provided evidence that, particularly in the United States, governments increase spending, or loosen monetary policy, prior to elections. In India, the evidence appears to be mixed. While Cole (2009) found that agricultural credit was expanded before elections, Khemani (2004) examined state political spending and found no change in the level of spending (or taxation). She does find some evidence of a compositional shift in taxes related to electoral cycles. We do not find an election year effect on disaster relief spending ( $p = 0.77$ ).

### *Robustness*

As our framework illustrates, the response to a rainfall shock is not the only signal that the voter observes. Our finding that voters are more likely to reelect an incumbent



who has responded well to an emergency may result from our measure of government responsiveness (rainfall shock interacted with relief spending) being correlated with 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 story is correct.

First, in Appendix Table 1 we add a number of controls at the state level to our preferred specification in Table 7 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, in Appendix Table 2 we add controls for political parties, to account for any systematic difference in administrative abilities across political parties. The results are consistent with those reported previously. Column (1) includes an indicator variable for whether Congress is the coalition leader; column (2) includes dummies for the three largest parties, INC (Congress), BJP (Bharatiya Janata Party), and JNP (Janata Party), and column (3) includes fixed-effects for all parties. In all cases, the coefficient on (rainfall SDs from optimal last year) \* (relief expenditure last year) remains statistically significant, though the precision of the main effects declines when a fixed effect is included for every ruling coalition party identity.

## **VII. Strategic Government**

The model in Section II assumed a benevolent government that, if competent, would respond to a crisis by distributing relief aid. A simple test of government response to crisis—and the voters’ reaction at the polls—was consistent with that view, although it remains possible that more complex strategies might be at play.

In this section we explore how voting behavior responds to weather not just in year prior to the election, but in earlier periods as well. This test is motivated by the well-

documented “recency” bias, identified in the psychology literature for over a century (Calkins 1896). Individuals consistently put greater weight on more recent events, even in situations where more recent events are no more informative than earlier events. Similar effects have long been observed with respect to voters’ responses to the events they observe as well (Fair 1978, Caplan 2007, Bartels 2008). While general government competence may well be correlated with the quality of crisis response, it is unlikely to be the case that this correlation exists only in the year before the election. On the other hand, voters may be better at recollecting government responses to crises that occurred more recently. We first establish that the recency bias exists in the electorate’s response to crises, then test the hypothesis that governments respond more vigorously with relief when the electoral rewards for doing so are greater.

In Table 8, we 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. In results that are available on request, we document that there is no relationship between rainfall two, three, or four years prior to an election, and electoral outcomes. However, no matter how many earlier years are included, the year before the election continues to enter in a statistically and economically significant manner.

Similarly, we find that, two years prior to a reelection, 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 that the coefficient on recent crisis response maintains its magnitude and significance, while for earlier years it is economically and statistically insignificant. This amounts to a rejection of our hypothesis that voters will use information from all available years of crisis response. Since voters are unlikely to observe multiple crises during the same period of office, this is strong evidence that this simple psychological bias causes significant failures in voters’ collective abilities to hold elected officials accountable for their actions.

This voter bias gives us an opportunity to test for non-naïve government relief. After all, if voters do not demand responsiveness of the government after particular crises (those, in this case, that do not occur in the year preceding an election), then the government may choose not to allocate resources towards disaster relief. Table 9 examines government spending on relief to bad rainfall, comparing election years with non-election years.

The first two columns in Table 9 repeat the main specifications in the first two columns of Table 6. With state and year fixed effects, we find that for each standard deviation by which rain deviates from the optimal amount, the government increases its disaster spending by 18 log points, or 19 percent. However, in columns (5) and (6), when we restrict attention to only election years, we find point estimates that are substantially higher than those in previous columns. In election years—when voters might be expected to pay more attention—the government’s generosity rises. In columns (3) and (4), we use all available data and include election year dummies as well as an interaction between election year and rainfall. The main effect is statistically significant, and the interaction term economically large and positive, but the interaction term is not statistically distinguishable from zero. We therefore take this as suggestive rather than definitive on this point.

While we cannot measure constituent welfare, it is quite likely that any strategic behavior of this sort is welfare-reducing: if the marginal returns to disaster relief decline with the level of spending, then voters may be better off when relief is targeted at years of severe drought, rather than years prior to an election.

Finally, we acknowledge an important caveat: if politician ability is highly time-varying, it may be rational for voters to pay more attention in the year immediately prior to the election. However, our estimate of a zero-effect two years before is relatively precise (we can rule out an effect of -1 percentage point, less than one-third the size of the electoral-year effect). If political ability changed this quickly, a forward-looking model of voting may not be appropriate.

We find evidence suggesting political opportunism in the time-series of aid provision: what about the cross-section? While Table 5 showed that voter response to rainfall shocks did not vary by voter sophistication, it is possible that voter

appreciativeness of government spending varies by sophistication. To test this hypothesis, we augment equation (7) with measures of district-level literacy, relief interacted with literacy, rain interacted with literacy, and a triple interaction relief \* literacy \* rain. In results we do not report (but which are available on request), we find that these additional terms are economically small and statistically insignificant.

What about politically-motivated targeting? As noted, we do not observe the exact geographies to which aid is targeted. It is, however, worth considering how the possibility of politically-motivated targeting may affect our results. If the voting population is risk-averse, optimal targeting would suggest that harder-hit areas should receive more relief than less-hard hit areas. It also seems reasonable that voters would provide the greatest reward to relief expenditure when it is most needed. However, it is worth noting that voters appear to respond substantially even to targeted spending that is largely pork (see, e.g., Levitt and Snyder, 1997). Empirically, it is an open question to what extent voters respond to spending that is more essential in comparison to spending that is more politically oriented.

If aid relief is simply pork distributed to regions in which the ruling coalition enjoys natural support, then areas that do not support the ruling coalition (e.g., opposition seats) would punish incumbent politicians' areas more than areas which strongly support the ruling coalition. We certainly did not observe this result in Table 4.

Regardless of the actual targeting used, our regression results give the average electoral response of voters. An interpretation of the fact that the electoral rewards to spending appear to be small is consistent with the idea that the aid is targeted not according to need, but rather towards areas that already support the ruling coalition. Thus, if voters actually do reward politically-oriented spending less than more essential spending, a government could potentially obtain higher electoral returns from relief spending by allocating those funds to areas that were more affected by disasters.

## **VIII. Conclusion**

This paper addresses longstanding questions about the relationship between exogenous events and political fortunes, studying tens of thousands of elections in India. We begin by outlining a simple framework to think about the problem. We first show that

voters may rationally punish politicians following negative shocks over which the politician has no control. This makes it difficult to isolate hypotheses about rationality in voters per se; however, it nonetheless provides an ideal setting to study the relationship between elected leaders and their constituents.

Using detailed weather, electoral, and relief data from India, we test hypotheses on electoral outcomes and government responsiveness to exogenous events. We find evidence that voters indeed punish incumbent politicians for economically significant events beyond the politician's control. Rainfall just one standard deviation from the optimal level reduces the incumbent coalitions vote share by 3.25 percentage points. The results are precisely estimated, using a conservative estimation technique which aggregates data to the district level and correct standard errors for clustering. We then use the richness of our data to shed light to the nuances of voter behavior, with four important and novel results.

First, we note that voters appear to be targeting their dissatisfaction: incumbent politicians who are members of the ruling coalition are punished severely following poor rainfall: a one-standard deviation decline in rainfall results in 2.6 percent fewer votes. In contrast, opposition incumbent legislators benefit from a 1.9 percentage point increase in voters for the same drop in rainfall. These results are important, because they suggest that traditional models of geography-based patronage thought to apply in the developing world may not accurately describe voting in India.

Second, we study whether voter characteristics mediate how voters respond to shocks. Some authors have posited that more sophisticated voters may be more able to process information, correctly assigning blame and credit to politicians for circumstances depending within the politicians' control, while filtering out exogenous events (e.g., Gomez and Wilson 2001). However, we find that voters' response to rainfall shocks does not vary with their level of education, nor even with the fraction of voters who are directly involved in agricultural production. These non-effects are precisely measured.

Third, we examine how voters' response to rainfall shocks varies with relief spending. Analyzing state-level natural disaster relief, we find that voters indeed punish governments less for poor weather when the government responds aggressively, but this mitigating effect is small. While we do not observe what drives variation in response, we

find it striking that even the most responsive governments suffer electorally following a bad rainfall shock.

Finally, we examine whether voters weigh all available information equally when evaluating governments in the wake of shocks. We find they do not: rainfall shocks in the year before an election hurt politicians, but rainfall in the year previous to that have no effect on the political fortunes of the incumbents. Similarly, we observe that relief spending two years prior to the election is not rewarded at all. This result is consistent with a model in which voters have limited memory.

Overall, these results tie together the findings of the literature on relief provision in democracies 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. Besley and Burgess (2002) noted that governments were more generous with relief to literate districts and those with more media outlets. Such a strategy plays to the intelligence and watchfulness of an electorate. We bring to this analysis a different strategy: since Indian voters, on average, punish their leaders for events beyond their control, we examine whether such behavior might feed into the provision of relief in India. The government's sharper focus on relief during election years plays not to the best qualities of democracy, but to the biases and forgetfulness of voters.

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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](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:** 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](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*).

During the period covered by our data, constituency boundaries were stable, allowing us to match constituencies over time and thus identify the political affiliation of the incumbent. 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.

**Disaster relief** spending: 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 Stuti 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: Inference of Politician Quality from Observed Outcomes**

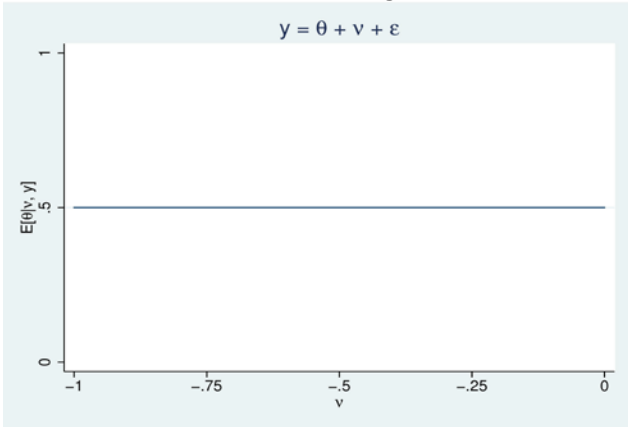


Figure 1a. This figure graphs the expected value of politician ability, when the weather shock  $v$  is observable, as a function of  $y$ , when unobserved ability  $\theta = 0.50$ , and the unobserved idiosyncratic shock  $\epsilon = 0.50$ . An increase in  $v$  has no effect on the expected value of  $\theta$ .

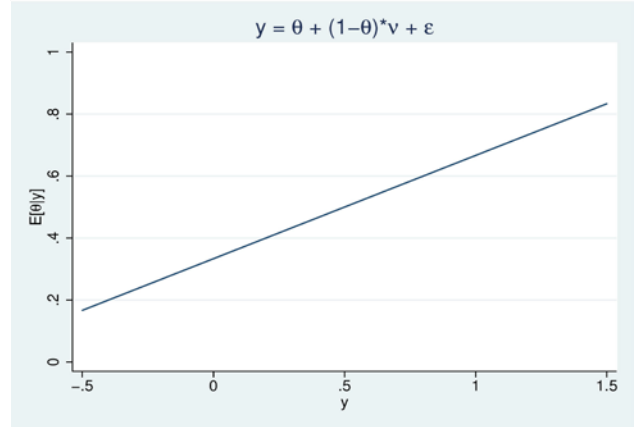


Figure 1b. This figure graphs the expected value of politician ability, when the weather shock  $v$  is unobservable, for the case when unobserved ability  $\theta = 0.50$ . For a given idiosyncratic shock  $\epsilon$ , an increase in  $v$  increases the voters' expected value of the politicians ability.

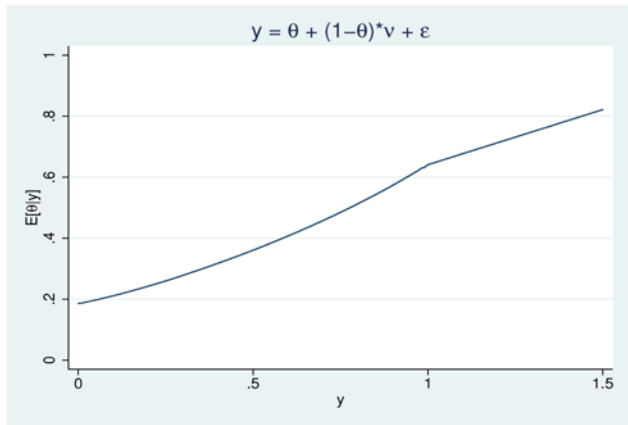


Figure 1c. This figure graphs the expected value of politician ability, when the weather shock  $v$  is unobservable and more able politicians are able to better mitigate the effects of the shock, as a function of  $y$ , for the case when unobserved ability  $\theta = 0.50$ .

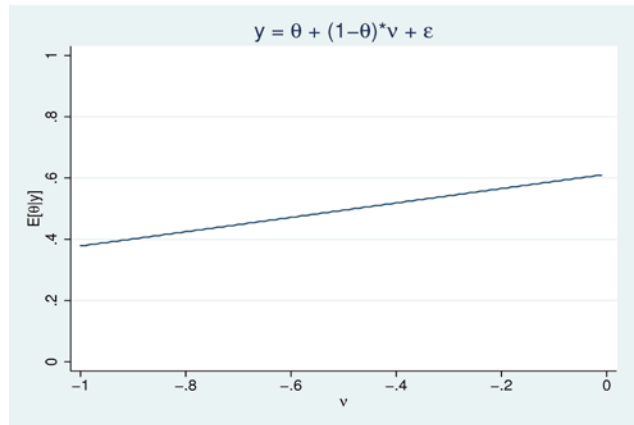


Figure 1d. This figure graphs the expected value of politician ability when the weather shock  $v$  is unobservable and more able politicians are able to better mitigate the effects of the shock, as a function of  $v$ , for the case when unobserved ability  $\theta = 0.50$ .

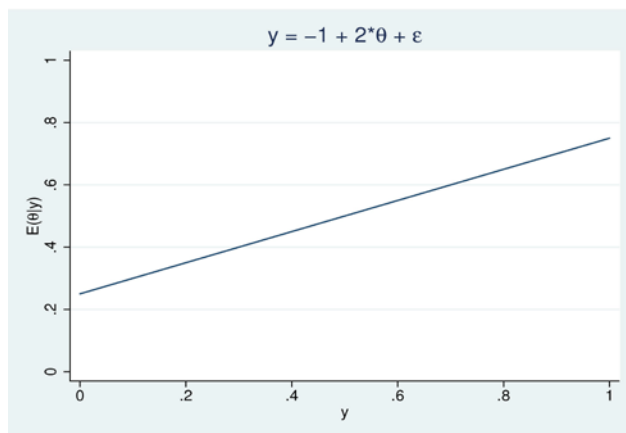
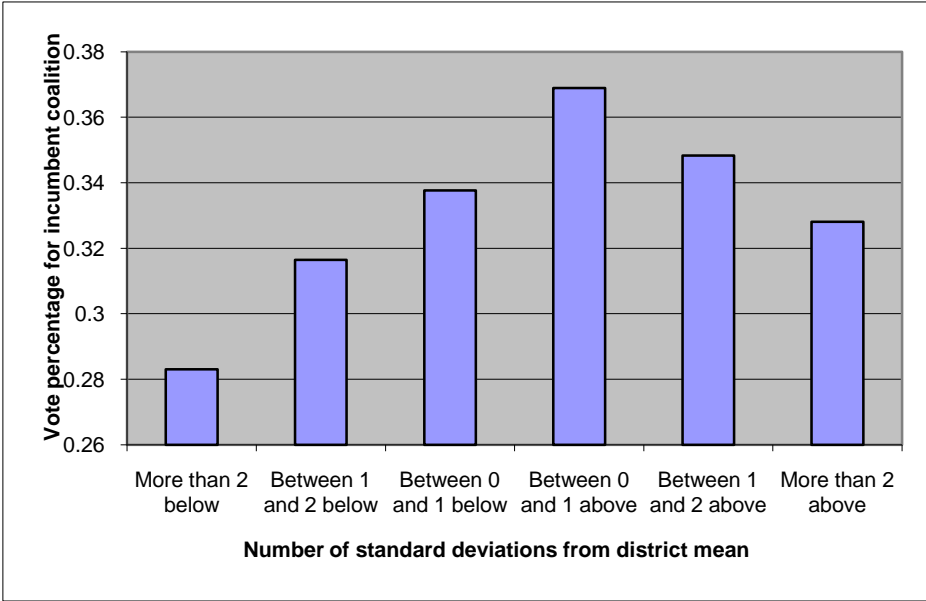
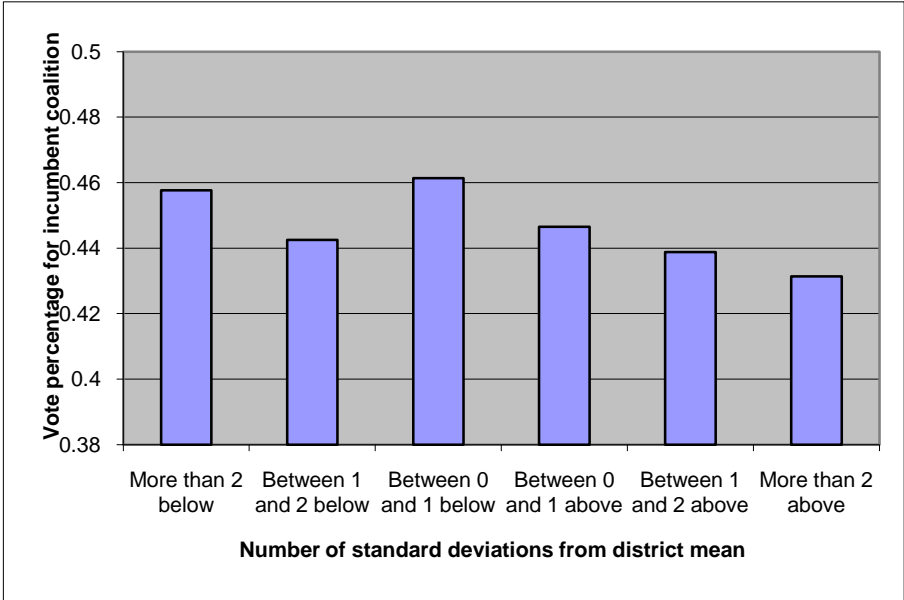


Figure 1e. This figure graphs the expected value of politician ability by an irrational voter, who does not recognize that rainfall shocks affect income, as a function of  $y$ , for the case where  $\theta = 0.50$ .

**Figure 2: Rainfall and Incumbent Coalition Voteshare**

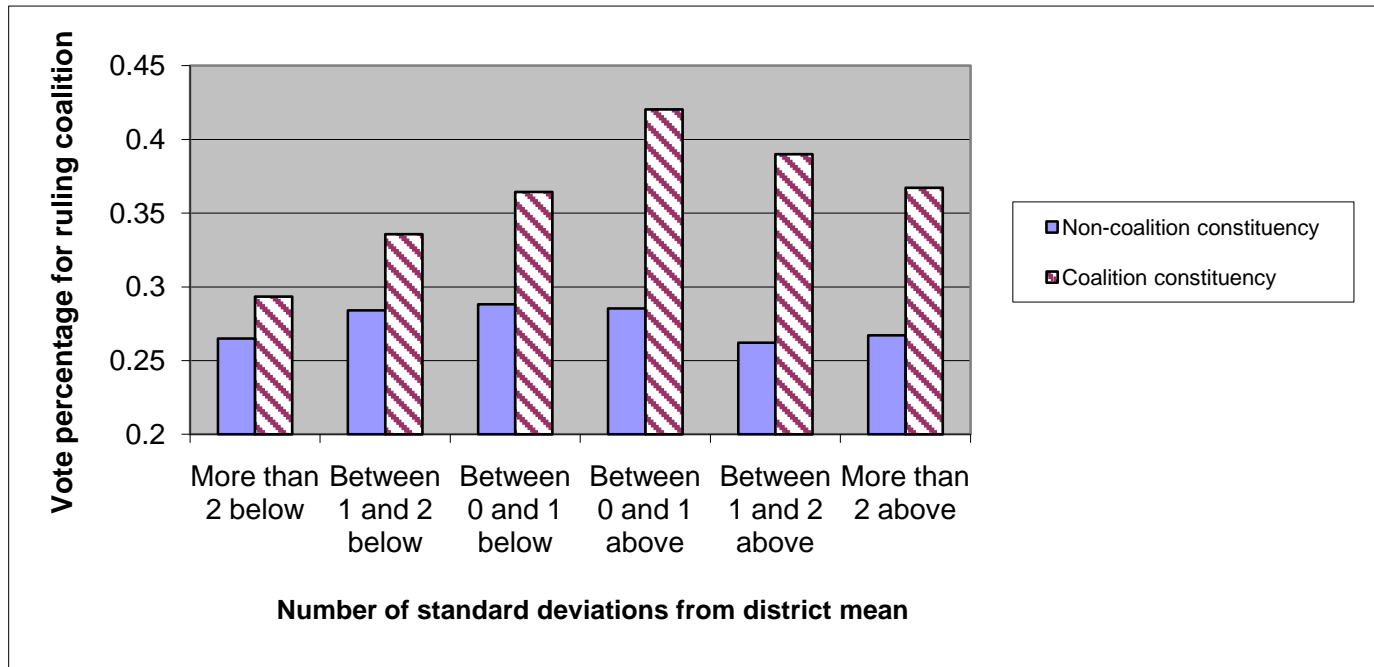


Panel A: Raw relationship between rainfall in a district in the previous year, and average vote share of incumbent coalition



Panel B: Falsification Exercise. Raw relationship between rainfall in a district in the previous year, and average vote share of incumbent coalition in the *previous* election

Figure 3: Rainfall and support for incumbent candidates, by coalition affiliation



The figure presents the raw relationship between vote share for the ruling coalition and rainfall, according to whether the coalition is incumbent in the constituency. The striped bars indicate vote share for the coalition when it is incumbent in the constituency. The solid bars indicate vote share for the ruling coalition when it does not hold in the constituency.

**Table 1: Summary statistics**

| Variable   | Mean  | S.D.  |
|--|-------|-------|
| <i>A. Voting variables</i>   |       |       |
| 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 in a constituency   | 35.3  | 15.5  |
| <i>B. District-Level Rainfall Measure</i>  |       |       |
| Kharif (June - September) rainfall in mm   | 995   | 667   |
| Standard deviation across districts (average Kharif rainfall)  | 91    |       |
| Fraction of rainfall variance explained by district fixed-effects<br>(R <sup>2</sup> of regression with district FE)       | .804  |       |
| Fraction of rainfall variance explained by year fixed-effects<br>(R <sup>2</sup> of regression with year FE)               | .018  |       |
| Fraction of rainfall variation explained by district and year fixed-effects<br>(R <sup>2</sup> of regression with year FE) | .823  |       |
| Percentage of observations for which rainfall is more<br>than two standard deviations from the optimal amount              | 18.3% |       |
| Percentage of observations for which rainfall is more<br>than three standard deviations from the optimal amount            | 1.1%  |       |
| <i>C. Disaster expenditure</i>   |       |       |
| 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<br>(Rain from June to September) | .0381<br>(4.41) | .035<br>(5.85) | .046<br>(4.76)    | .0449<br>(6.62)   |                   |                   |
| (Normalized Kharif Rainfall)^2                              |                 |                | -.0142<br>(-2.61) | -.0177<br>(-4.69) |                   |                   |
| Standard deviations of kharif rain<br>from optimal          |                 |                |                   |                   | -.0584<br>(-4.95) | -.0538<br>(-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              |
| <i>N</i>  | 14108           | 14108          | 14108             | 14108             | 14108             | 14108             |

Notes:

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

**Table 3: 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<br>(Rain from June to September)       | .0253<br>(2.92) | .0229<br>(2.27) | .0291<br>(3.2)    | .0275<br>(2.62)   |                   |                   |
| Kharif rain <sup>2</sup>                           |                 |                 | -.0073<br>(-2.17) | -.0092<br>(-2.33) |                   |                   |
| Standard deviations of kharif rain<br>from optimal |                 |                 |                   |                   | -.0331<br>(-3.29) | -.0325<br>(-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              |
| <i>N</i>   | 2091            | 2091            | 2091              | 2091              | 2091              | 2091              |

Notes:

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



**Table 4: Affiliation with Ruling Coalition and the Effect of Weather on Electoral Outcomes**

|   | Constituency level vote shares:     |                   |  |                   |  |                 |
|---|-------------------------------------|-------------------|--|-------------------|--|-----------------|
|   | For all parties in ruling coalition |                   | Incumbent legislator, where legislator is member of ruling coalition |                   | Incumbent legislator, where legislator is not part of ruling coalition |                 |
|   | (1)                                 | (2)               | (3)  | (4)               | (5)  | (6)             |
| Standard deviations of kharif rain from optimal | -.038<br>(-3.56)                    | -.0375<br>(-3.32) | -.0223<br>(-2.45)  | -.0255<br>(-2.68) | .0203<br>(2.01)  | .0191<br>(1.51) |
| State dummies?                                  | Y                                   | N                 | Y  | N                 | Y  | N               |
| District dummies?                               | N                                   | Y                 | N  | Y                 | N  | Y               |
| R-squared                                       | .14                                 | .184              | .41  | .433              | .288   | .365            |
| <i>N</i>  | 21532                               | 21532             | 17994  | 17994             | 4656   | 4656            |

Notes:

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

**Table 5: Voter Characteristics and the Relationship Between Rainfall and Electoral Support**

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

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

Notes:

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

**Table 6: Rain's effect on disaster spending (1960-1999)***Dependent variable: Log of State per-capita natural calamity relief expenditure*

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

Notes:

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

**Table 7: Weather, voting, and relief expenditure**

| <i>Dependent variable:</i>   | <i>Ruling Coalition</i> |                  | <i>Ruling Coalition</i> |                   | <i>Ruling Coalition</i> |                    |
|--|-------------------------|------------------|-------------------------|-------------------|-------------------------|--------------------|
|  | <i>Vote Share</i>       |                  | <i>Vote Share</i>       |                   | <i>Seat Share</i>       |                    |
|  | <i>District Level</i>   |                  | <i>State Level</i>      |                   | <i>State Level</i>      |                    |
|  | <i>(1)</i>              | <i>(2)</i>       | <i>(3)</i>              | <i>(4)</i>        | <i>(5)</i>              | <i>(6)</i>         |
| Standard deviations of kharif rain from optimal last year                      | -.0386<br>(-4.08)       | -.036<br>(-3.28) | -.0706<br>(-2.14)       | -.0791<br>(-2.97) | -0.1360<br>(-1.03)      | -0.2218<br>(-1.71) |
| ln (relief expenditure last year)  | .0063<br>(.35)          | .0077<br>(.38)   | .0095<br>(.55)          | .0012<br>(.05)    | -0.0001<br>(0.00)       | 0.0768<br>(0.75)   |
| ln (relief expenditure last year) * standard deviations from optimal last year | .0222<br>(2.35)         | .0291<br>(3.3)   | .0313<br>(1.24)         | .0373<br>(1.74)   | -0.0332<br>(-0.79)      | -0.0783<br>(-1.44) |
| State dummies?   | Y                       | N                | N                       | Y                 | N                       | Y                  |
| District dummies?  | N                       | Y                | N                       | N                 | N                       | N                  |
| R-squared  | .387                    | .503             | .373                    | .578              | 0.418                   | 0.644              |
| <i>N</i>   | 1756                    | 1756             | 79                      | 79                | 79                      | 79                 |

Notes:

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

**Table 8: Weather, voting, and relief expenditure***Dependent variable: Vote share in the district for the ruling coalition*

|   | (1)               | (2)               | (3)               | (4)               |
|---|-------------------|-------------------|-------------------|-------------------|
| Standard deviations of kharif rain<br>from optimal last year  | -.0335<br>(-3.32) | -.0325<br>(-2.78) | -.0383<br>(-4.2)  | -.0356<br>(-3.39) |
| ln (relief expenditure last year)   |                   |                   | .0139<br>(.71)    | .0149<br>(.69)    |
| ln (relief expenditure last year) *<br>standard deviations from optimal last year                   |                   |                   | .0229<br>(2.45)   | .0295<br>(3.45)   |
| Standard deviations of kharif rain<br>from optimal two years previous                               | .0094<br>(1.03)   | .0101<br>(1.05)   | .0084<br>(.92)    | .0059<br>(.62)    |
| ln (relief expenditure two years previous)  |                   |                   | -.0061<br>(-.31)  | -.008<br>(-.38)   |
| ln (relief expenditure two years previous) *<br>standard deviations from optimal two years previous |                   |                   | -.0091<br>(-1.19) | -.0075<br>(-.99)  |
| State dummies?  | Y                 | N                 | Y                 | N                 |
| District dummies?   | N                 | Y                 | N                 | Y                 |
| R-squared   | .356              | .456              | .393              | .508              |
| N   | 2091              | 2091              | 1756              | 1756              |

Notes:

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

**Table 9: Rain's effect on disaster spending (1960-1999)***Dependent variable: Log of State per-capita natural calamity relief expenditure*

|   | (1)               | (2)               | (3)              | (4)              | (5)             | (6)             |
|---|-------------------|-------------------|------------------|------------------|-----------------|-----------------|
| Kharif rain<br>(Rain from June to September)                | -.1726<br>(-3.04) | -.1289<br>(-2.41) |                  |                  |                 |                 |
| Kharif rain <sup>2</sup>                                    |                   |                   |                  |                  |                 |                 |
| Standard deviations of kharif rain<br>from the optimal      |                   |                   | .2206<br>(2.27)  | .1389<br>(1.47)  |                 |                 |
| Election dummy  |                   |                   | -.0652<br>(-.27) | -.1415<br>(-.63) |                 |                 |
| Election*Standard deviations of<br>kharif rain from optimal |                   |                   | .101<br>(.54)    | .1533<br>(.86)   | .3891<br>(2.39) | .4533<br>(2.98) |
| State dummies?  | Y                 | Y                 | Y                | Y                | Y               | Y               |
| Year dummies?   | N                 | Y                 | N                | Y                | N               | Y               |
| R-squared   | .657              | .691              | .658             | .692             | .688            | .745            |
| <i>N</i>  | 551               | 551               | 551              | 551              | 128             | 128             |

**Notes:**

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

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

**Notes:**

1) The rain variables are all standardized subtracting the district mean and dividing by the district standard deviation.

2) *t*-statistics are in parentheses. Standard errors are corrected for clustering at the state\*year level.

3) All regressions include year dummies.

4) Regressions are weighted by the number of votes in the district.

**Appendix Table 2: Rainfall and Incumbent Support, Controlling for Party Identity**

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

|  | (1)               | (2)              | (3)               |
|--|-------------------|------------------|-------------------|
| Standard deviations of kharif rain from optimal last year                      | -.0273<br>(-2.35) | -.018<br>(-1.49) | -.0064<br>(-.76)  |
| ln (relief expenditure last year)  | .0054<br>(.30)    | .0093<br>(.54)   | -.0144<br>(-1.03) |
| ln (relief expenditure last year) * standard deviations from optimal last year | .0191<br>(2.77)   | .021<br>(2.30)   | .0217<br>(2.72)   |
| R-squared  | .543              | .564             | .667              |
| Party Fixed Effects  | INC Party         | INC, BJP, JNP    | All parties       |
| <i>N</i>   | 1756              | 1756             | 1756              |

Notes:

- 1) The rain variables are all standardized subtracting the district mean and dividing by the district standard deviation.
- 2) *t*-statistics are in parentheses. Standard errors are corrected for clustering at the state\*year level.
- 3) All regressions include year dummies.
- 4) Regressions are weighted by the number of votes in the district.
- 5) Column (1) includes a dummy indicating whether Congress (INC) was the coalition leader; column (2) includes a dummy for each of the three largest parties, INC, BJP, and JNP; and column (3) includes a separate dummy variable for each party that was a coalition leader.