Do Voters Demand Responsive Governments? Evidence from Indian Disaster Relief[*]

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ABSTRACT:

Using rainfall, public relief, and election data from India, we examine how governments respond to adverse shocks and how voters react to these responses. The data show that voters punish the incumbent party for weather events beyond its control. However, fewer voters punish the ruling party when its government responds vigorously to the crisis, indicating that voters reward the government for responding to disasters. We also find evidence suggesting that voters only respond to rainfall and government relief efforts during the year immediately preceding the election. In accordance with these electoral incentives, governments appear to be more generous with disaster relief in election years. These results describe how failures in electoral accountability can lead to suboptimal policy outcomes.

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.[1]

This example suggests an omitted analysis from the 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

[1] "How Ballot Hopes Rest on Good Monsoon**,**" Financial Express, April 21, 2003.

and Malhotra (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 is 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 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 significantly punished only 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 first 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 outlines the conceptual framework that guides our empirical analysis. 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. Conceptual Framework

In this section we describe a framework within which we analyze how voters respond to government action following a crisis. This framework forms the basis for our empirical tests.

Framing the reelection decision

A fundamental purpose of democracy is to allow voters to choose competent leadership by rewarding good governments with reelection, and punishing bad governments by voting them out at the polls. There are a variety of formal models of democratic accountability (see for example, Acemoglu and Robinson, 2006). Rather than developing a new one, we instead sketch what we believe as the most straightforward model of voters, who utilize all available information, including the governmental response to crisis, to decide whether to reelect a government.[2]

We consider a government that seeks to respond to crises by providing relief aid, potentially motivated both by concern for constituent welfare, and out of concern for winning reelection.

[2] Undoubtedly, there are more complex formulations of the principal-agent relationship between voters and their governments in which our framework's predictions are violated yet all actors behave rationally. In this paper we seek to explore the simplest model. Our focus is not to prove that some or all voters behave or do not behave rationally, but rather to establish and test a benchmark case.

Consider the following timeline:

1. A government of unknown competence is elected.
2. The government implements non-disaster policies.
3. It rains (or not). The amount of rainfall is random, drawn from the distribution for the district.
4. The government responds with some quantity of relief aid.
5. Voters observe their own welfare, rainfall, relief aid, and other government policies.
6. Steps 2 and 5 are repeated for each year until the next election occurs.
7. At the time of reelection, voters decide whether to vote for the incumbent or for a new government of unknown competence.

In this simplified framework, we note the possibility that voters learn about government competence by observing how the government responds to disasters. As the extensive literature on political business cycles has demonstrated, there are multiple plausible ways to interpret economic booms, budget deficits, and even monetary policy in the election cycle (Drazen, 2000). Voters may view these variables as partly attributable to competence, and partly to strategy. Such gamesmanship is possible with relief aid as well, but it is reasonable to imagine that in the Indian context relief is easier to observe than fiscal policy and state transfers—let alone industrial policy or other policies possibly important for welfare, but far removed from the experiences of a typical agrarian voter.

Four predictions follow immediately from this simple framework (see Table A). One, bad rainfall should not result in the punishment of politicians, on average. Since learning is most plausibly symmetric (politicians could improve or tarnish their image, depending on their response to a crisis), on average voters will feel better about a politician half the time, and worse about the politician the other half of the time. This suggests there should be no mean electoral consequences to a natural disaster.

Table A: Hypotheses with a rational electorate

H1: Weather will not affect voting outcomes, on average.
H2: Governments respond to bad rainfall with relief.
H3: Voters will reward governments for above-average disaster relief.
H4: Voters will reward government disaster relief no matter in which year of the election cycle it occurs.

Second, because voters infer competence from government reaction to crises, we predict that governments will respond to crises with relief aid. Third, in turn, voters will reward a government that has vigorously responded to a disaster more than one that has not. While seemingly obvious, these tests have nonetheless been omitted from most other previous studies.

Our final hypothesis relates to the timing of relief aid and the electoral cycle. We assume that voters interested in measuring competence use all information available, and in particular pay attention to relief aid distributed in both election years and non-elections. Since severe disasters are by definition rare events, in many cases voters will have at most one opportunity to learn government competence through the crisis-response channel, and this opportunity will not necessarily fall in an election year.[3]

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.

[3] We acknowledge that this stands in contrast to the canonical models in political budget cycles literature, in which politicians optimally distort

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 understand better 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.

India has a federal system of government, with a bicameral national legislature, but typically unicameral state legislatures.[4] 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.

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

The first state and federal elections were held in 1951, shortly after the promulgation of India's constitution. Parliamentary elections are scheduled to occur at five-year intervals, but as in other parliamentary systems, may be called earlier.[5]

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, 2008, for examples.) In Russia, such manipulations have been shown to aid re-election (Akhmedov and Zhuravskaya, 2004).

Politics and parties

The Indian National Congress Party, which led the independence movement, initially dominated Indian politics, 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 is from the Election Commission of India. Unless otherwise noted, we aggregate voting outcomes up from the constituency level to the district level.[6] There

[5] 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).

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.[7] We account for spatial correlation of error terms by clustering results at the state-election level; the results are robust to clustering at the state level (available upon request). Data on agricultural output, from Sanghi, Kumar, and McKinsey (1998), provide the quantity, yield, and price for 25 of the most common agricultural crops in India. The dataset runs from 1950 to 1994; for the subsequent years, we use an updated version created by Rohini Pande.[8]

Combining these datasets, we conduct all analysis, unless otherwise noted, at the district-election level.[9] 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

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[6] We do this to ensure our standard errors are conservative—we observe rainfall variation only at the district level.

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

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

[9] 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.

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 25th percentile is 639 and the 75th percentile 1176.

Panel B also reports the share of variation in rainfall explained by year and district fixed-effects. While geography, unsurprisingly, explains a 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 monsoon period.[10] 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.[11]

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.[12] The next section demonstrates that the optimal level of rainfall is about one standard deviation above the mean.

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[10] 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.
[11] 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.
[12] 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.

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:

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

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

$$(2) \qquad VoteShare_{dct} = \alpha + \gamma_d + \tau_t + \beta{*}weather_{dt-1} + e_{dt}$$

$VoteShare_{dct}$ is the vote share in a constituency c for the candidate from the incumbent ruling party. We use the previous year's weather, as the main kharif season is from June to September, while the elections typically occur in February and March. Thus the rain in the calendar year before the election is the most salient.[13] This equation will allow us to test, in the Indian context, the general hypothesis of Achen and Bartels (2004) and Healy (2008), that incumbents are punished for "acts of God" in the time leading up to their election.

[13] We will study the role of earlier rainfall below.

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 irrational-voter tests in our Indian context. We find that abnormally low or high rain in a district leads to lower agricultural output. On average, 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).[14] Table 2 tests variations of equation (1), using the natural log of the total value of crop yield as the dependent variable.[15] 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

[14] Adjusting for inflation is not necessary, as all the regressions include year fixed-effects.

[15] We use the sum of the value of the 25 most common crops, as reported in the Willmott and Matsuura data.

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.[16]

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 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. Figure 1 gives the average vote share of the ruling party by rainfall category: the bar graph gives the mean for each indicated bin; the line gives results from a non-parametric regression. The ruling party does very poorly during extreme droughts, but its performance increases steadily with rainfall, reaching an optimum at a point between 0

[16] 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.

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, 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 cause 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.

These results stand in sharp contrast to hypothesis H1, which posited that observable, exogenous shocks do not systematically affect the electoral fortunes of politicians. 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 2 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 line). 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).

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 as a 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 interpretation 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) add 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.

One possible explanation for these results is "attribution bias," by which individuals attribute success or failure to the actions of a particular individual, even when the situation or circumstances are the primary determinant of an outcome. Weber et al. (2001), for example, demonstrates experimental subjects attribute success or failure in a coordination game to the quality of a randomly selected leader, rather than the exogenously imposed group size.

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.

$$(3) \qquad Relief_{st} = \alpha + \gamma_s + \tau_t + \eta * TotalSpending_{st} + \beta * \overline{Weather}_{st-1} + e_{st}$$

In the above equation, we take the mean of the weather variable across the state in a given year. We lag weather because the Indian fiscal year ends on March 31. Thus, relief spending for the 2000 fiscal year, represents spending in the twelve months from April 1999 to March 2000. We therefore relate relief spending from April 1999 to March 2000 to weather from May 1999 to October 1999, the most recent monsoon season. We expect our coefficients on weather to be the opposite from those in equation (1): more extreme weather should generate higher relief spending.[17] Table 6 tests various specifications for equation (3), using the different definitions of *weather* outlined in Section IV.

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

[17] 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.

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.

The results are entirely consistent with prediction H2.

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.[18]

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

If voters do respond to the presence of disaster spending in the face of bad weather, then we would expect that δ would be positive in the above regressions.[19] We note that there is tremendous heterogeneity in government response, and the variance in relief spending increases in the severity of the weather.

The first two columns of Table 7 report the results of estimating equation (4). We find that voters do indeed reward politicians for disaster spending in response to extreme weather, with δ positive, and consistently significant across all specifications. In the third 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 δ is positive, of a similar magnitude as with the district-level regressions, and marginally statistically significant (*t*-statistic of 1.74).

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 Table 7, we estimate that a party which

[18] We do not lag relief expenditures because they correspond to the fiscal year leading up to the calendar year – thus covering the rainy season under analysis.
[19] Khemani (2004) finds that overall state expenditure does not vary in election years, although the composition of taxes does. We do not find an election year effect on disaster relief spending (p = 0.77).

responds to bad rainfall with an average increase in disaster spending will gain about 0.52 percentage points of vote share (0.178*2.91) compared to a coalition that does not increase its disaster response when the weather shock occurs. Since a one standard deviation worsening in weather costs the incumbent party 3.25 percentage points of the vote share on average, failing to respond in the face of a crisis should lead to an average reduction of votes of 3.77 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 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. On balance, this evidence appears to reject our third hypothesis, that voters reward politicians who offer strong responses to crises. 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.

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, BJP, and JNP, and column (3) includes fixed-effects for all parties. In all cases, the coefficient on (rainfall deficit 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 framework 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; however, it remains possible that more complex strategies might be at play. In this section we test for strategic disaster-relief spending on the part of incumbent governments in India.

Our test of this hypothesis derives from the well-documented "recency" bias, identified in the psychology literature for over a century (Calkins 1896), that individuals put greater weight on more recent 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 is likely correlated with the quality of crisis response, it is unlikely to be correlated with crises only in certain years. On the other hand, voters may be better at recollecting government responses to crises that occurred more recently. We first establish that the recency bias exists in the electorate's response to crises, then test a fifth hypothesis that easily follows from the framework in which the government is non-naïve.

H5: 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. Similarly, we find that in the earlier year there is no relationship between vote share for the incumbent coalition and our measure of responsiveness, the interaction between relief expenditure and rainfall (columns (3) and (4)). If our measures were picking up general competence of the government, we might expect the same relationship throughout the electoral cycle, or for the coefficient on responsiveness in the year prior to the election to diminish. Yet we find 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 fourth 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 repeat the main specifications from Table 9. 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. But as columns 9 and 10 show, when we restrict our analysis to election years—when voters actually pay attention—the government's generosity rises. With the year dummies, the same standard deviation in rain fall from optimal leads to an increase in relief aid of 45 log points, or 57 percent. This is evidence consistent with H5: the government, on average, appears to be strategically distributing relief according to the voters' biases. In contrast to the policies that would be implied by public welfare maximization, Indian policymakers appear to give voters what they ask for.

While we cannot measure constituent welfare, it is quite likely that this strategic behavior 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.

VIII. Conclusion

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 are guilty of attribution bias: they punish incumbent politicians for economically significant events beyond their control. Introducing a simple framework, we ask whether voters reward their leaders for good administration during such crises. We find that voters do reward leaders for correctly responding to climatic events in India, although in general not to a degree sufficient to compensate for the politician's "bad luck" for having presided over a crisis. In this setting, Indian voters exhibit a recency bias—only punishing and rewarding governments for crises and responses in the year preceding the election. Strategically, governmental response is more vigorous to rainfall shocks that occur during election years.

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. The database provides rainfall at a .5 degree by .5 degree grid. A degree of latitude is approximately 69 miles.

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

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

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

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

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

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

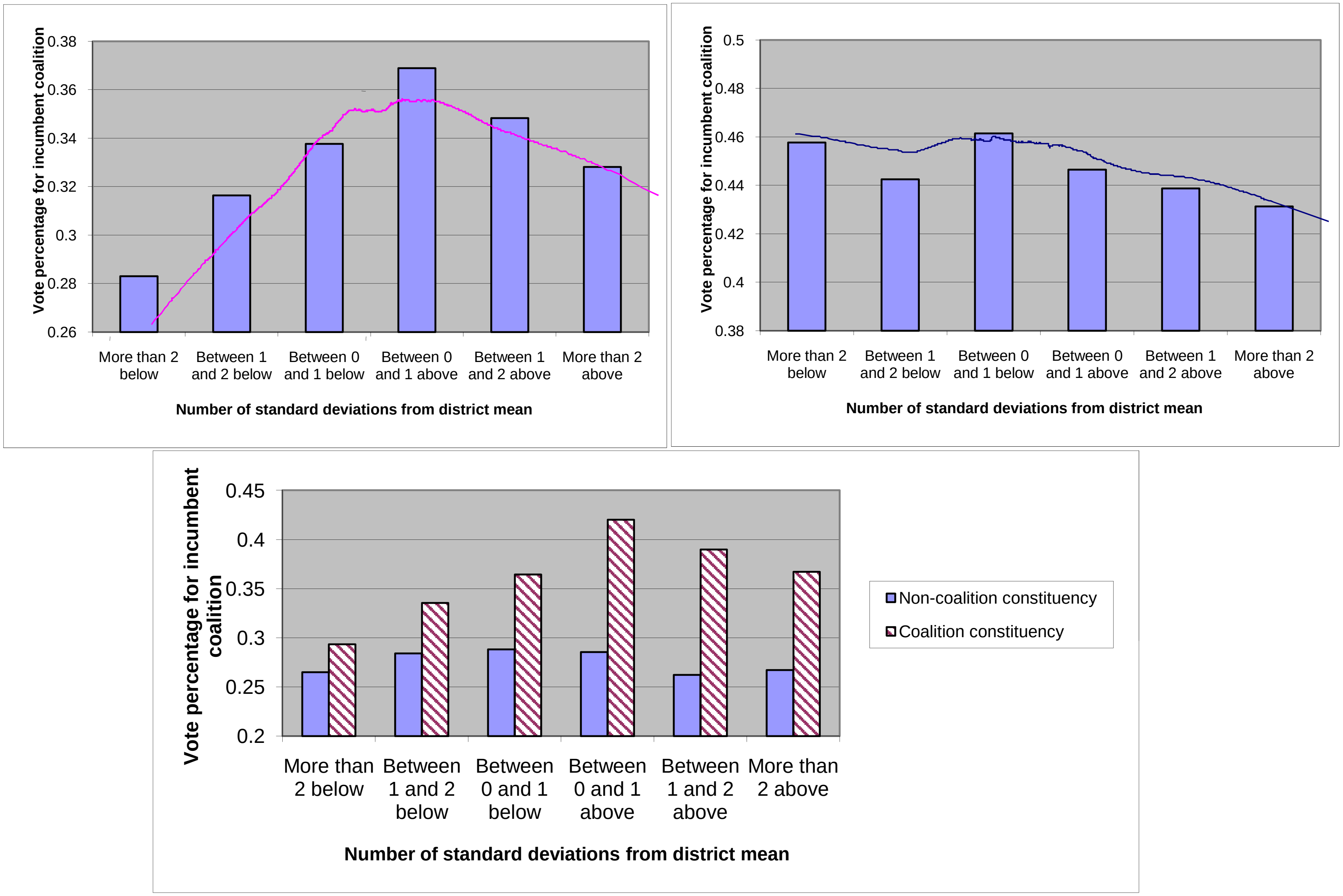

Figure 1: Relating rain to the ruling coalition and incumbent party vote percentage

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

Figure 2: Vote share for the state ruling coalition when it is and is not defending the constituency seat

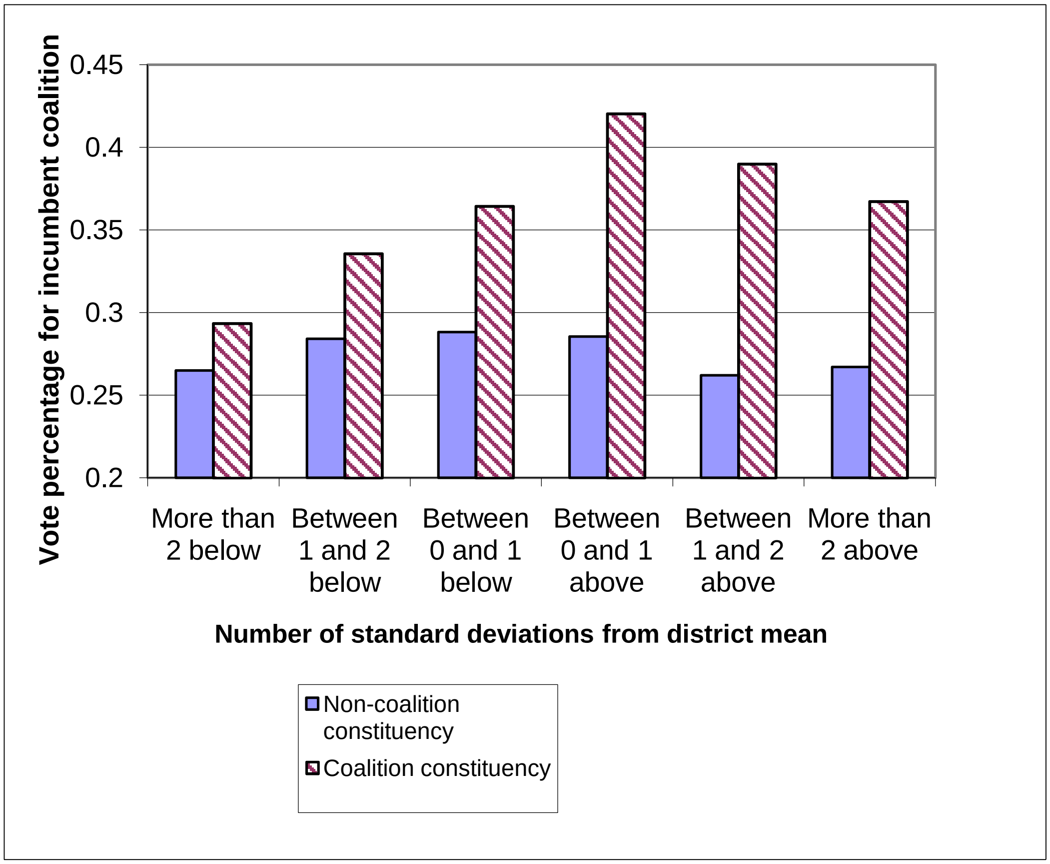

Table 1: Summary statistics

Variable	Mean	S.D.
A. Voting variables		
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
B. District-Level Rainfall Measure		
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 (R^2 of regression with district FE)	.804	
Fraction of rainfall variance explained by year fixed-effects (R^2 of regression with year FE)	.018	
Fraction of rainfall variation explained by district and year fixed-effects (R^2 of regression with year FE)	.823	
Percentage of observations for which rainfall is more than two standard deviations from the optimal amount	18.3%	
Percentage of observations for which rainfall is more than three standard deviations from the optimal amount	1.1%	
C. Disaster expenditure		
Per-capita average expenditure (Rs/person)	10.3	11.8

Table 2: Effect of rain on crop yields (1956-1987)

Dependent variable: Log of total crop value

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

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

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	-.0375	-.0223	-.0255	.0203	.0191
	(-3.56)	(-3.32)	(-2.45)	(-2.68)	(2.01)	(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
N	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	-.0346	-.0328	-.0377	-.0389	-.0377	-.0379
(Rain in June-September year before the election)	(-3.49)	(-2.79)	(-3.27)	(-2.67)	(-3.01)	(-2.43)
District farm share	.0313	-.3045			.0253	-.4291
	(.96)	(-1.6)			(.33)	(-2.19)
District farm share*Standard deviations of rain from optimal	-.0106	-.0367			.0027	-.0084
	(-.42)	(-1.11)			(.06)	(-.14)
District literacy rate			-.0485	.0303	-.0146	-.2106
			(-.67)	(.08)	(-.11)	(-.52)
District literacy rate*Standard deviations of rain from optimal			.0265	.0587	.0297	.0541
			(.53)	(.94)	(.36)	(.56)
State dummies?	Y	N	Y	N	Y	N
District dummies?	N	Y	N	Y	N	Y
R-squared	.36	.46	.356	.456	.356	.459
N	2063	2063	2026	2026	2026	2026

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)	(7)	(8)	(9)	(10)
Kharif rain	-.1726	-.1289	-.1914	-.1429						
(Rain from June to September)	(-3.04)	(-2.41)	(-3.12)	(-2.47)						
Kharif rain^2			.0681	.0489						
			(1.32)	(1.00)						
Standard deviations of kharif rain					.2458	.1775	.2206	.1389		
from the optimal					(3.00)	(2.28)	(2.27)	(1.47)		
Election dummy							-.0652	-.1415		
							(-.27)	(-.63)		
Election*Standard deviations of							.101	.1533	.3891	.4533
kharif rain from optimal							(.54)	(.86)	(2.39)	(2.98)
State dummies?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummies?	N	Y	N	Y	N	Y	N	Y	N	Y
R-squared	.657	.691	.658	.692	.657	.691	.658	.692	.688	.745
N	551	551	551	551	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.

Table 7: Weather, voting, and relief expenditure

Dependent variable: Vote share in for the ruling coalition

	District Level		State Level	
	(1)	(2)	(3)	(4)
Standard deviations of kharif rain	-.0386	-.036	-.0706	-.0791
from optimal last year	(-4.08)	(-3.28)	(-2.14)	(-2.97)
ln (relief expenditure last year)	.0063	.0077	.0095	.0012
	(.35)	(.38)	(.55)	(.05)
ln (relief expenditure last year) *	.0222	.0291	.0313	.0373
standard deviations from optimal last year	(2.35)	(3.3)	(1.24)	(1.74)
State dummies?	Y	N	N	Y
District dummies?	N	Y		
R-squared	.387	.503	.373	.578
N	1756	1756	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 from optimal last year	-.0335 (-3.32)	-.0325 (-2.78)	-.0383 (-4.2)	-.0356 (-3.39)
ln (relief expenditure last year)			.0139 (.71)	.0149 (.69)
ln (relief expenditure last year) * standard deviations from optimal last year			.0229 (2.45)	.0295 (3.45)
Standard deviations of kharif rain from optimal two years previous	.0094 (1.03)	.0101 (1.05)	.0084 (.92)	.0059 (.62)
ln (relief expenditure two years previous)			-.0061 (-.31)	-.008 (-.38)
ln (relief expenditure two years previous) * standard deviations from optimal two years previous			-.0091 (-1.19)	-.0075 (-.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)	(7)	(8)	(9)	(10)
Kharif rain	-.1726	-.1289	-.1914	-.1429						
(Rain from June to September)	(-3.04)	(-2.41)	(-3.12)	(-2.47)						
Kharif rain^2			.0681	.0489						
			(1.32)	(1.00)						
Standard deviations of kharif rain					.2458	.1775	.2206	.1389		
from the optimal					(3.00)	(2.28)	(2.27)	(1.47)		
Election dummy							-.0652	-.1415		
							(-.27)	(-.63)		
Election*Standard deviations of							.101	.1533	.3891	.4533
kharif rain from optimal							(.54)	(.86)	(2.39)	(2.98)
State dummies?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummies?	N	Y	N	Y	N	Y	N	Y	N	Y
R-squared	.657	.691	.658	.692	.657	.691	.658	.692	.688	.745
N	551	551	551	551	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	-.0296	-.0267	-.0282	-.0246
from optimal last year	(-2.84)	(-2.34)	(-2.64)	(-2.12)
ln (relief expenditure last year)	.007	.0102	.0054	.0061
	(.36)	(.48)	(.29)	(.29)
ln (relief expenditure last year) *	.0249	.0268	.0203	.0276
standard deviations from optimal last year	(2.85)	(2.42)	(1.7)	(2.65)
State GDP growth in the previous year	.3003	.3024	.3507	.3669
	(1.28)	(1.25)	(1.63)	(1.51)
Change in cash balances (in thousands)		-.0015	-.0014	-.0011
		(-.7)	(-.74)	(-.53)
Budget deficit (in thousands)			.0016	.0016
			(1.76)	(1.52)
Population growth				-2.699
				(-.29)
State dummies?	N	N	N	N
District dummies?	Y	Y	Y	Y
R-squared	.512	.496	.396	.507
N	1756	1605	1605	1605

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	-.018	-.0064
	(-2.35)	(-1.49)	(-.76)
ln (relief expenditure last year)	.0054	.0093	-.0144
	(.30)	(.54)	(-1.03)
ln (relief expenditure last year) * standard deviations from optimal last year	.0191	.021	.0217
	(2.77)	(2.30)	(2.72)
R-squared	.543	.564	.667
Party Fixed Effects	INC Party	INC, BJP, JNP	All parties
N	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 larest parties, INC, BJP, and JNP; and column (3) includes a separate dummy variable for each party that was a coalition leader.