The Politics of Drought Relief: Evidence from Southern India*

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Abstract

A core function of government is to provide assistance to households affected by negative shocks. This paper studies such government intervention in the form of drought relief in three Indian states. I demonstrate that while states' targeting of relief partly aligns with environmental measures of drought, it does not strictly adhere to national guidelines for allocating drought relief. Instead, allocations are disrupted by the political motivations of the state ruling party. The likelihood of an area receiving relief increases in the electoral competition faced by the ruling party while political alignment with the ruling party reduces the likelihood of receiving relief. A dynamic probabilistic voting model explains these results. I confirm that the associations I report reflect a causal relationship by utilizing an instrumental variables approach and regression discontinuity design. Finally, the paper provides evidence suggesting that the mistargeting of relief results in a misallocation of public resources.

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1 Introduction

In developing countries, and particularly so in rural areas, there is an inextricable link between livelihoods and the environment. Natural disasters, such as drought, therefore threaten the livelihoods of these households.[1] Climate change threatens to alter the timing, duration, intensity, frequency, and spatial distribution of such events (IPCC, 2012). Governments then are likely to play an increasingly critical role, providing assistance to households affected by such negative shocks. However, as with many functions of government, the degree to which a government successfully provides this aid depends on its responsiveness to citizens' needs. Sen (2000) points to the importance of democracy in linking the incentives of agents (e.g., the disaster-affected) and political incentives through electoral accountability. But even within democracies, public programs may be subject to political manipulation. An important question then is whether the discretionary power of government, which enables this politicization, furthers or obstructs the success of a program.

This paper studies the targeting of drought relief in three Indian states. I document the degree to which relief is targeted on the basis of official measures of need and the extent to which allocations are distorted due to political motives. The paper then addresses the efficacy of drought relief, establishing a positive link between relief and agricultural production. Importantly, the paper provides evidence suggestive of misallocation, demonstrating that enforcing the national guidelines for targeting relief would increase aggregate agricultural production.

Effective drought relief is of particular importance in India, a highly drought-prone region that is heavily reliant on rainfed agriculture. In recognizing this, India has developed a comprehensive drought management program that incorporates relief as well as drought mitigation and adaptation strategies (UNDP, 2002). Relief measures encompassed by this program include food and water provision, direct cash transfers, and increased public employment. A key feature in the evolution of India's program is the movement towards a rules-based allocation. India's program then stands apart from those in the US, for example, which explicitly incorporate discretion (Downton & Pielke, 2001). A report on a predecessor to India's current program cites the lack of a clear, objective definition of drought as leaving room for political manipulation (Rathore, 2005). The Indian government responded by issuing national guidelines that base the allocation of relief on environmental criteria (DAC, 2009).

In this paper, I study the allocation of official drought declarations, or an indicator that

[1]Previous work connects natural disasters to significant economic and health consequences across every region of the world (Ranson et al., 2016; Stanke et al., 2013).

an area received drought relief, in the states of Karnataka, Andhra Pradesh, and Telangana. I construct a panel dataset of declarations for 1,284 blocks (groups of villages) for the years 2008 through 2019 and combine it with geospatial environmental data and electoral data. In spite of the national government's increasingly stringent guidelines and increased public scrutiny, this paper shows that states' allocation of declarations regularly breaks with guidelines. During this period 1 in 4 declarations went to blocks with above-average rainfall, well above rainfall cutoffs defining drought. In the same period, 1 in 3 drought-affected blocks did not receive relief.

The paper provides a dynamic probabilistic voting model as a framework for assessing the potential politicization of drought relief. First, I assume that voters associate drought relief with the state government and so increase their electoral support for the state ruling party if they receive relief.[2] Second, I allow for a shock to voters' electoral support for the ruling party in areas the ruling party previously won (aligned areas), which I refer to as a ruling-party incumbency effect.[3] The ruling party then decides whether or not to allocate drought relief to each area in an effort to maximize its reelection likelihood, subject to the marginal cost of providing relief. The model generates three testable implications: (1) drought increases the likelihood of receiving drought relief, (2) the likelihood of receiving relief is increasing in the electoral competition faced by the ruling party (how close a vote margin the ruling party previously won/lost by), and (3) a ruling-party incumbency effect creates a discontinuity in the electoral returns to the ruling party for providing drought relief between politically aligned (previously won) and non-aligned (previously lost) areas.

I extend the traditional probabilistic voting model to a dynamic setting, which reveals omitted variable bias in naive regressions of the likelihood of receiving a declaration (relief) on electoral outcomes. Solving the model shows that the past behavior of politicians (i.e., declaration allocations) influences current political decisions through its impact on electoral outcomes (violation of sequential exogeneity). To overcome this model-implied bias, I utilize variation in electoral competition for the ruling party and political alignment that is uncorrelated with prior declarations. I instrument for a party's vote share in a given election using the interaction of local support for the party in an election prior to the sample period with a state level change in political support that excludes local changes driven by these past declarations. The instrument for the ruling party's vote margin (electoral competition) is then just the difference between the

[2] Existing research and media reports link drought declarations, and political manipulation, with the state government (Poovanna, 2016; Rathore, 2005; Reddy, 2016; Bera & Sen, 2016). Cole et al. (2012) tests the salience of this link and finds that voters reward the state ruling party for disaster relief.

[3] Prior work identifies important incumbency advantages/disadvantages for local politicians in Indian elections (Anagol & Fujiwara, 2014; Fisman et al., 2019; Linden, 2004).

ruling party's and its opposition's instrumented vote shares.[4] I utilize a close election regression discontinuity design to identify the effects of political alignment on declaration likelihood, which assumes that politically aligned areas and non-aligned areas with close elections are similar in their unobservable characteristics (e.g., past declarations).

As predicted by the model, drought occurrence increases the likelihood of receiving a declaration by 18 percentage points, relative to a mean likelihood of 33 percent; therefore, in practice, the drought-affected are more likely to receive drought relief. In contrast to much of the recent work on distributive politics in India, I find that areas aligned with the state ruling party are *less* likely to receive drought relief, which is instead targeted to areas that are electorally competitive for the ruling party. Consistent with the model, electoral competition for the ruling party increases the likelihood of receiving relief: a one standard deviation increase in competition for the ruling party increases declaration likelihood by 9 percentage points. Alignment with the ruling party reduces the likelihood of receiving relief, with a negative discontinuity in declaration likelihood between non-aligned and aligned areas. These patterns of distributive politics in which political connections reduce the likelihood of receiving relief might seem surprising but are explained by the model. The fact that aligned areas are less likely to receive relief (negative discontinuity) results from a ruling-party incumbency advantage, or a positive shock to the ruling party's reelection likelihood in aligned areas regardless of providing relief.

In sum, official drought declarations do not strictly adhere to national guidelines meant to ensure the appropriate targeting of relief. Moreover, the paper causally identifies political manipulation as one mechanism for this mistargeting. However, it is still possible that states use their discretion to provide an efficient allocation of drought relief based on private information. A small subset of existing work in the distributive politics literature addresses this concern by going a step further to estimate the potential welfare costs of identified political distortions. A novel contribution of this paper is how it addresses a related question: does the mistargeting of drought relief *relative to guidelines* represent a misallocation of public resources?[5]

While a difficult question to answer, I make progress towards determining whether drought relief is in fact misallocated by estimating the impact of declarations on local agricultural production.[6] I find that a prior-year declaration is associated with 6 percent higher agricultural

[4]This instrument largely follows that used by Shaukat (2019), though its exact construction differs, and also relates to George (2020) where, again, the author instruments for political competition.

[5]This question is particularly policy-relevant given the Indian government's recent decision to move to a rules-based allocation, strictly enforcing these guidelines.

[6]Following Asher and Novosad (2020), I use a proxy for block-level agricultural production constructed from the difference between early-season and maximum normalized difference vegetation index values.

production in non-drought-affected blocks but 11 percent higher production in drought-affected blocks. First, this estimated increase in agricultural production associated with a prior-year declaration is not a trivial result. Recent work shows that one of India's other public programs targeting rural development, access to rural roads, has no effect on agricultural outcomes (Asher & Novosad, 2020). Second, this positive association is higher when declarations are appropriately targeted. This finding suggests the existence of misallocation that could be resolved through the enforcement of national guidelines. These results hold across a series of robustness checks and specifications testing alternative explanations for the findings.

I also consider the differential effect of declarations across the distribution of prior-year local rainfall shocks (as opposed to only comparing drought-stricken blocks and all other blocks). I find a distinct u-shape in the effect of prior-year declarations on agricultural production across this distribution: the positive effect is highest in drought-affected areas (left-tail rainfall shock), not statistically different from 0 in areas with normal rainfall (center of distribution), and relatively high in areas that experienced excessive rainfall (right-tail rainfall shock).[7] Taking these results at face value, reallocating declarations to the 35 percent of blocks experiencing severe negative rainfall shocks that did not receive a declaration would result in 10 percent higher agricultural production in each of these blocks. Removing declarations from the blocks with normal or just above normal rainfall (25 percent of all declarations) does not impact agricultural production in those blocks. These findings suggest significant misallocation under the assumption that drought-affected blocks that received a declaration are the relevant counterfactual for drought-affected blocks that did not receive a declaration.

Related Literature. This paper sits at the intersection of two vast and important literatures, the first focuses on decentralization and targeting and the second considers the political manipulation of public resource allocations. Previous work on disaster relief similarly situates itself at this intersection.[8] Similar to this paper, Downton and Pielke (2001) finds that US flood relief simultaneously correlates with environmental measures, defining appropriate targeting, and political measures. Mirroring the results for official drought declarations in India, Garrett and Sobel (2003) demonstrates that the likelihood of receiving an official disaster declaration in the US is higher in electorally important states (electorally competitive). The main point of departure in this paper then is the identification of a robust, causal link between electoral incentives and official disaster declarations as opposed to focusing only on correlations. Two

[7] India has a separate flood relief program but these results suggest the need for relief in cases of excessive rainfall, which may or may not coincide with flooding.

[8] Oliver and Reeves (2015) discusses existing research on the politicization of disaster relief.

other papers seek to causally identify the impact of political motives on the provision of disaster relief, as I do here, but utilize alternative methods for identifying disaster-affected areas. Azulai (2017) studies ministerial grants to areas reported as disaster-affected in Brazil while Shenoy and Zimmermann (2020) considers public employment provision to areas located near a river that experienced flooding in West Bengal. On the other hand, I utilize a range of environmental, satellite, and agricultural data to identify and control for disaster severity when causally identifying the impact of electoral incentives on drought relief.

A primary focus of the decentralization literature is determining whether targeting is improved by decentralizing implementation of a public program.[9] Alatas et al. (2012) conducts an experiment in Indonesia to test alternative methods for targeting the poor, comparing proxy means testing against community-based identification of poor households. Similarly, Mookherjee and Nath (2020) considers moving from discretion-based to formula-based allocations for anti-poverty programs in West Bengal. The tradeoff tested in these papers is loss of local knowledge when allocating resources under the formulaic approach against manipulation of allocations under local discretion. Taken together, Mookherjee and Nath (2020) and Alatas et al. (2012) suggest, at best, moderate gains in pro-poor targeting from imposing formula-based approaches. I assess a similar tradeoff but consider a different type of targeting: in the context studied here, need is measured by disaster occurrence (a shock) as opposed to household demographic characteristics (poverty). Publicly-available environmental measures of drought are less likely to be reliant on the addition of local government knowledge for accuracy; consistent with this assumption, the findings of this paper suggest that targeting in line with national guidelines has the potential for significant improvements in agricultural outcomes.

Within the distributive politics literature, this paper closely relates to existing work studying the allocation of public programs to competitive or politically aligned constituencies and even more narrowly to those considering such political manipulation for electoral gain (Asher & Novosad, 2017; Azulai, 2017; Bardhan et al., 2020; Cole, 2009; Finan & Mazzocco, 2020; Gupta & Mukhopadhyay, 2016; Sarkar, 2019; Shaukat, 2019; Shenoy & Zimmermann, 2020).[10] In this paper, I demonstrate that the state ruling party targets relief to areas in which it faces higher electoral competition and *not* to aligned areas. These patterns for political manipulation of drought relief differ from recent work on the allocation of public programs in West Bengal. Shenoy and Zimmermann (2020) finds that alignment of local leaders with the state ruling party increases allocations of a public program while Bardhan et al. (2020) shows that allocations

[9] Mookherjee (2015) provides an overview of the decentralization literature.

[10] Golden and Min (2013) reviews and classifies existing work on distributive politics.

depend jointly on alignment and electoral competition. The difference in results between this paper and others does not necessarily suggest a lack of external validity for the findings on political manipulation. Instead, this variation highlights the importance of identifying two facets of a public program when studying patterns of distributive politics: (1) the level of government controlling the allocation of the program and (2) the level of government with which voters associate the program. For example, a comparison of this paper with Bardhan et al. (2020) might suggest that the variation in targeting is driven by voters rewarding the state for drought relief but local politicians for the welfare programs considered in West Bengal.

This paper also connects to work studying political manipulation in the case of rules-based public programs. Banful (2011) and Ward and John (1999) study formula-based transfers from national to local governments, where the national government sets the formula; in these cases, transfers might perfectly comply with the formula but the authors argue that the national government politically manipulates the formula itself. This paper's setting largely precludes this type of manipulation because the national government sets the rules by which state governments should make drought relief decisions. In spite of this separation of power, I causally identify political manipulation by states even when using the national guidelines as a guidepost against which declarations can be compared. Finally, while many papers consider the political manipulation of public resources, few address the potential costs of this manipulation. Azulai (2017) estimates a small bias due to political distortions for ministerial grant allocations in Brazil, leading to a relatively small amount of misallocation. Finan and Mazzocco (2020) studies allocations of legislative funds in a Brazilian state and estimates large distortions away from an area with low electoral returns but high expected welfare gains, resulting in a large misallocation. In this paper, I show that some drought-affected areas, where expected welfare gains are likely high, do not receive drought relief while some non-drought-affected areas do receive relief. However, I move beyond this result to consider whether drought relief has an impact on observed local economic outcomes. I provide evidence suggestive of misallocation by identifying a positive association between relief and agricultural production *if* relief is well-targeted.

The remainder of the paper proceeds as follows. Section 2 introduces the context and assesses the extent to which declarations follow guidelines. Section 3 models the state's declaration decision and Section 4 details the empirical strategy and identification approach used to test the model's implications. Section 5 provides empirical results identifying the causal impact of the ruling party's electoral incentives on the allocation of drought relief. Section 6 describes the impacts of drought relief on local development and Section 7 concludes.

2 Context

India is one of the most drought prone regions in the world and yet more than half of India's net cultivated area is directly reliant on rainfall (DAC&FW, 2017; UNDP, 2002). Existing literature shows that natural disasters, and drought specifically, can lead households to resort to distress sales (Cain, 1981; Kinsey et al., 1998), migration (Boustan et al., 2019; Gray & Mueller, 2012), or even reductions in consumption and diet quality (Carpena, 2019; Kazianga & Udry, 2006). In India, the negative impacts of drought, perhaps in combination with household responses, then manifest in cases of stunted, wasted, and underweight children as well as chronic energy deficiency in adults; further, India reported one of the highest levels of drought-related mortality between 1900 and 2012 (Stanke et al., 2013). India's drought management program is a response to this combined high level of exposure and high degree of vulnerability to drought. The program has evolved to not only provide post-disaster relief but also incorporate mitigation and adaptation strategies aimed at reducing vulnerability to future drought (UNDP, 2002).

This paper studies India's drought management program in 1,284 blocks[11] located in Karnataka (2008-2019) and Andhra Pradesh/Telangana (2009-2019). I construct an indicator for whether a block received a declaration (non-zero relief) for the primary growing season (June to September) using government-provided data (see Appendix B).[12] During this period, the Indian government provided drought relief guidelines in the 2009 Manual for Drought Management, 2016 updated manual, and subsequent revisions to the 2016 manual (DAC, 2009; DAC&FW, 2016; DAC&FW, 2018), which states cite in declaration decisions (GoAP, 2013; Reddy, 2016).

2.1 Environmental Criteria and Data

The drought manuals list rainfall deficiency as the primary basis for declaration decisions. According to the 2009 Drought Manual, a declaration should be considered if: (1) the ratio of total June/July rainfall to its long-term-average is less than 50 percent or (2) the ratio of total June-September rainfall to its long-term-average is less than 75 percent. Combining these two criteria and using the India Meteorological Department rainfall data (Pai et al., 2014), the indicator for a block being drought affected is

$$drought_{bt} = \mathbf{1}\{ratio_{bt}^{June/July} < .5 \vee ratio_{bt}^{June-Sept} < .75\}.$$ [13]

[11] The administrative unit, located between districts and villages, at which declarations are made.

[12] In recent years, states have declared drought for the secondary growing season between October and January.

[13] Appendix B provides further details on the construction of this indicator, additional rainfall measures, and variables for the other environmental categories. Also in this appendix is a description of alternative criteria for defining drought-affected blocks using updates to the drought manuals and state-level guidelines.

Because of the primacy of rainfall measures in the national guidelines, combined with the fact that rainfall is exogenously determined, I use this measures to define drought-affected areas. Figure 1 depicts annual variation both in drought and declarations by state. The manuals also list additional environmental factors to be used in declaration decisions: cropped area, vegetation indices (remote sensing), soil moisture indices, and hydrological indices. Where satisfying rainfall-based criteria is a necessary condition for drought declarations, meeting cutoffs in these remaining categories provides sufficient evidence of drought. Section 5.1.2 demonstrates robustness of the paper's main results when controlling for these additional environmental factors.

2.2 Administrative Process and Political Data

According to the national guidelines, the decision to officially declare a block as drought-affected should proceed in two steps. First, the district collector forms a committee to determine which blocks in the district are drought-affected. Second, each district sends its list to the state government where, again, a committee chooses blocks from each list to receive declarations. If followed, this procedure assigns the ultimate decision-making power to the state.[14]

Elections for members to the state legislative assembly (MLAs) occur (about) every five years and are based on a first-past-the-post election system.[15] The party or coalition that wins a majority of seats forms the government (referred to here as the ruling party). As shown in Figure 1, the sample period includes three elections for each state beginning in 2008 for Karnataka and 2009 for Andhra Pradesh/Telangana.[16] The figure highlights the variation in the ruling parties in power both within and across states; this provides a context for studying the importance of the ruling party's political motives, as opposed to political party-specific behavior. For this analysis, I utilize data from the Election Commission of India (2019) and Bhavnani (2014) on electoral outcomes to construct two variables that measure support for the ruling party. First, I use the vote share for each party $p \in P$ that runs in a constituency c and election e to generate a variable for the ruling party r's vote margin as

$$margin_{ce} = voteshare^{r}_{ce} - max_{p \neq r}\{voteshare^{p}_{ce}\}.$$

In the case of a ruling coalition, for each constituency I compare the vote share for the party in the coalition that had the highest vote share to the vote share of the opposition party (the party

[14]Only the final list of blocks, used here, determines official declarations and is made available to the public.
[15]Andhra Pradesh and Telangana have a bicameral system, but the legislative council is not directly elected.
[16]Andhra Pradesh and Telangana become separate states in 2014, the second election in this period.

with the highest vote share among those not in the coalition).[17] If the ruling party did not run in a constituency, it's vote share is set to 0. I then take the absolute value of the margin, which is a measure of electoral competition for the ruling party (as $|margin|$ approaches 0, competition increases). Second, I construct an indicator for alignment to the ruling party as

$$aligned_{ce} = \mathbf{1}\{margin_{ce} > 0\}.$$

This alignment indicator designates whether the ruling party won in a constituency and, therefore, will be an incumbent in the following election. This measure of ruling-party incumbency may also provide relevant information for reelection likelihood; for example, voters' might increase their support for the ruling party in areas where the ruling party won and the local politician belongs to the ruling party (i.e., ruling-party incumbency advantage). Appendix B provides the mapping of these constituency-level variables to block-level variables as well as information on additional political variables used in robustness checks. Table 1 provides summary statistics at the block-year level for the above measures.

2.3 Local Development Data

Once an area receives a declaration, formal drought relief measures are initiated. States provide relief in a number of forms, such as input subsidies (cash transfers), livestock camps, water/food provision, public employment, and loan deferment (DAC, 2009; DAC&FW, 2016). While loan deferments might only benefit those with prior bank access, input subsidies and increased public employment target all households. In the same way that drought might have serious consequences throughout the local economy, drought relief then has the potential for aggregate effects. To study the extent of relief's impacts, I utilize data on agricultural production as it is a primary driver of local rural economies;[18] it is also the first sector affected by drought and, unsurprisingly, directly targeted by relief (e.g., input subsidies to farmers).

Data on agricultural output is only publicly available for districts, which contain 26 blocks on average. To study agricultural production at the block level, I follow Asher and Novosad (2020) in constructing a proxy for agricultural production based on the normalized difference vegetation index (NDVI) (a satellite-based measure of plant growth density). For each year 2008 to 2019, I proxy for crop growth by taking the season maximum of the NDVI and subtracting the

[17] For Karnataka, I assign the BJP as the ruling party in the 2008 election (6 independent candidates were in the coalition) and the INC and JD(S) in the 2018 election (1 BSP candidate helped form the ruling coalition).

[18] During the 2012 agricultural year, more than half of rural households in India were classified as agricultural households and that figure does not include households entirely reliant on agricultural labor for employment (NSSO, 2014).

early-season NDVI (average NDVI over the first three 16-day periods in the season), where the difference is meant to account for non-crop vegetation. Asher and Novosad (2020) demonstrates that this measure is a relevant proxy, showing it is significantly, positively correlated with measures of agricultural production in Indian villages.

2.4 Do drought declarations adhere to national guidelines?

Are drought declarations simply explained by drought occurrence? On average, about 33 percent of block-year observations receive an official drought declaration while 18 percent are drought-affected (Table 1). In other words, more blocks receive drought relief than are drought-affected, suggesting that drought occurrence is not a necessary condition for observed drought declarations. Figure 1 provides a more detailed comparison, plotting the share of blocks, for each state and year, which received a declaration in combination with the share of blocks affected by drought; as shown, a significant number of declarations go to non-drought-affected blocks. Part of this mistargeting could be explained by small differences between state governments' rainfall data and that of the national government, used here, that would be especially pronounced in an indicator measure.[19] For this reason, I also consider how the likelihood of a declaration varies in continuous measures of rainfall. Figure 2 plots the ratio of current June-September rainfall to its long-term average (x-axis) against the ratio of June/July rainfall to its long-term average (y-axis). Again, based on the guidelines, we should expect a discontinuity in declarations at the black vertical line (marking a June-September ratio of .75) and at the black horizontal line (marking a June/July ratio of .5), as shown in Panel A. However, Panels B and C of the figure which plot only declared and only non-declared blocks, respectively, show a lack of such discontinuities. Instead, declarations are provided to block-year observations far from either cutoff while some observations that met both cutoffs did not receive a declaration. These results indicate that while variation in rainfall partly explains the allocation of drought declarations, states do not *strictly* follow the criteria outlined in the national guidelines.

3 Model

If the national guidelines are not strictly followed, what else might explain variation in declarations? As described previously, the state government ultimately determines declarations and so the model I formulate in this section focuses on the reelection motives of the ruling party. While

[19] As an example, the correlation between Karnataka's block-level data for June-September rainfall in 2018 and the block-level rainfall constructed using national data is .94.

the model proposed here is similar to that provided by Dixit and Londregan (1996) in that it can be resolved into a swing-constituency model, the assumptions that underlie this model differ from those used in a traditional probabilistic voting model. First, the model incorporates a ruling-party incumbency effect to explain differential targeting of declarations based on alignment to the ruling party. Second, I extend the traditional model to a dynamic framework to identify potential endogeneity concerns in empirical tests of the model's implications.

I consider a two-party model in which candidates from each party run in each constituency and the party with the most winning candidates forms the state government. Elections then are separated by a governing period during which the ruling party implements the drought relief program by allocating declarations to constituencies. The model begins with an election in period $t = 0$, so then for $t \in \{0, 1, 2, 3, 4, ...\}$ even-numbered periods represent elections and odd-numbered periods represent governing periods.

Voter's Preferences

In each constituency c, a voter of type i prefers party p over the opposition party if

$$\varphi_{ip} > 0,$$

where φ_{ip}, voter i's intrinsic preference for party p relative to the opposition, is uniformly distributed with probability density function $\frac{1}{\delta_i}$ and mean $\bar{\varphi}_{ip}$.[20] The parameter value φ_{ip} then represents the difference between individual i's utility when party p wins and when the opposition wins the election so that $\varphi_{ip} > 0$ indicates voter i's utility is higher when party p is elected. Assuming the world begins at $t = 0$, in this first election the vote share for party p in constituency c is

$$v^0_{pc} = \frac{1}{2} + \sum_{i \in I} \beta_{ic} \frac{\bar{\varphi}_{ip}}{\delta_i}$$

where β_{ic} is the fraction of type $i \in I$ voters in constituency c.[21] The party p candidate wins in the constituency if $\sum_i \beta_{ic} \frac{\bar{\varphi}_{ip}}{\delta_i} > 0$, or the population-weighted average intrinsic support favors the party p candidate. The party that wins the election in a majority of constituencies $c \in C$ then becomes the ruling party r and governs before running against the opposition party in the next election.

During the governing period $t = 1$, a drought might occur and the ruling party decides whether or not to allocate a drought declaration to each constituency. Therefore, in the second

[20] For all voter types, the support of the distribution is such that $0 \in [\bar{\varphi}_{ip} - \frac{\delta_i}{2}, \bar{\varphi}_{ip} + \frac{\delta_i}{2}]$.

[21] For example, constituencies may vary in their share of rural versus non-rural voters.

election, a voter of type i will vote for the ruling party r if

$$\sigma_{ir}^2 \equiv \varphi_{ir} + \delta_i[f_r(d_c^1, r_c^1) + \zeta(v_{cr}^0) + \epsilon_c^2] > 0,$$

where f_r is the function that translates voter utility over the state of the world in terms of drought occurrence $d_c^t \in \{0,1\}$ and receipt of a declaration $r_c^t \in \{0,1\}$ into a transitory shift in voters' support for the ruling party; I assume that this shift lasts one period and therefore only impacts preferences in the election that immediately follows the governing period. I include the function $\zeta(v_{cr}^t) = \zeta \times (\mathbf{1}\{v_{cr}^t > \frac{1}{2}\} - \mathbf{1}\{v_{cr}^t < \frac{1}{2}\})$ to account for a ruling-party incumbency advantage ($\zeta > 0$) or disadvantage ($\zeta < 0$).[22] Consistent with existing empirical evidence on candidate-level incumbency effects in India, I assume that the magnitude of an incumbency effect is not too large, or $|\zeta| < .15$ (Anagol & Fujiwara, 2014; Fisman et al., 2019; Linden, 2004).[23] Again, the shift in voters' support for the ruling party due to incumbency naturally lasts for a single period. On the other hand, I also allow for a normally-distributed, common shock to voters' support for the ruling party, $\epsilon_{cr}^t \sim \Phi(0, \nu^2)$, that occurs immediately before the following election.[24] Because shocks occur between governing periods and the following election, there is no shock during governing periods $t \in \{1, 3, 5, ...\}$. This is a permanent shock to voters' support for the ruling party and can be thought of as voters learning about how the party's platform affects their constituency through its governance.

Voter's Response to Drought Declarations

Drought is defined here as a negative deviation in rainfall from its long-term average, which reduces agricultural production (see Table 7) and likely negatively impacts other sources of income for rural households. For this reason, I assume that drought results in a negative shock to voters' consumption. On the other hand, drought relief is a positive wealth shock which I assume voters associate with the state government and, therefore, results in a temporary increase in support for the ruling party. These assumptions result in the following function translating voter utility from drought declarations into voter preferences,

$$f_r(d_c^t, r_c^t) = \theta_r(d_c^t) r_c^t,$$

[22] An advantage might result from voters' increased affinity for the ruling party in constituencies where it is in power but could also indicate the ruling party's ability to manipulate votes/elections where it is the incumbent.

[23] A constituency-election level regression of the indicator for whether the ruling party is reelected on the indicator for whether the incumbent politician is a member of the ruling party suggests ruling-party incumbency is associated with a 13 percentage point advantage in reelection likelihood.

[24] The assumptions on the distribution of the shock $\Phi(\cdot)$ important for the model implications are that it is mean-zero, single-peaked, and symmetric; also, the variance cannot be too large (e.g., $\nu < .3$). The subscript r indicates the shock is relative to the ruling party (a positive shock for r is a negative shock for the opposition).

where $\theta_r(d_c^t) \in (0, 0.1]$ is the positive shift in support for the ruling party associated with receiving a drought declaration.[25] Finally, I assume that voter's utility is increasing and concave in consumption so that the marginal utility from relief is higher for drought-affected voters. This increased marginal utility results in a greater increase in support, or $\theta_r(1) > \theta_r(0)$.

Ruling Party's Allocation Decision

In governing period t the ruling party's vote share for the following election is

$$v_{cr}^{t+1} = v_{cr}^{t-1} + L(\theta_{r'}, \zeta_{r'}) + \theta_r(d_c^t) r_c^t + \zeta(v_{cr}^{t-1}) + \epsilon_{cr}^{t+1}.$$[26]

The ruling party observes three signals for how it will perform in the upcoming election. First, the ruling party perfectly observes the vote margin from the prior election (v_{cr}^{t-1}). However, because this vote share was affected by temporary shifts in support for the $t-3$ ruling party r' due to past declarations and incumbency, the vote share is adjusted as follows

$$L(\theta_{r'}, \zeta_{r'}) = \left[\theta_{r'}(d_c^{t-2}) r_c^{t-2} + \zeta(v_{cr'}^{t-3})\right] \times \left[\mathbf{1}\{r \neq r'\} - \mathbf{1}\{r = r'\}\right].$$

For example, the function L accounts for a declaration temporarily increasing support for the prior ruling party and so adjusts the vote share downward (upward) if the ruling party in t is the same (different). Given that ϵ is mean-zero, the observed vote share, v_{cr}^{t-1}, and this adjusted vote share, $v_{cr}^{t-1} + L(\theta_{r'}, \zeta_{r'})$, act as signals for expected performance in the following election. Second, the party knows whether it is an incumbent in period t and is aware of an incumbency advantage (or disadvantage). Third, I assume that the ruling party and voters alike observe drought and declarations, so that the ruling party anticipates voters' response to declarations.

Turning to the motives of the ruling party, I assume that the sole goal of the party is to be reelected, which is achieved by the party's candidates winning reelection in a sufficient number of constituencies. Therefore, after winning the election and becoming the ruling party, in governing period t the party chooses whether or not to provide an official drought declaration in a given constituency c according to

$$\max_{r_c^t} \Pr(v_{cr}^{t+1} > \frac{1}{2}) \quad \text{subject to} \quad \sum_{c=1}^{C} r_c^t \leq N^t. \tag{1}$$

[25] Cole et al. (2012) considers the effect on the state ruling party's vote share of an increase in state-level disaster funds corresponding to a standard deviation shock in rainfall from normal. While considering a different question, this is the closest empirical evidence for assessing the likely magnitude of $\theta_r(d^t)$. That paper finds an effect on the vote share of less than 1 percentage point and so I impose an upper bound on $\theta_r(d^t)$ that suggests moderate shifts in support due to a declaration.

[26] Appendix A contains a detailed description of how voter's preferences are generalized to a governing period t and derives this equation for the ruling party's vote share in that period.

I assume that the cost of a declaration is constant across constituencies and, therefore, the government's budget constraint can be thought of as a limit on the number of declarations made in each year, N^t.[27] Allowing η^t to represent the Lagrange multiplier and assuming the distribution of ϵ is such that it guarantees σ_{ir}^{t+1} is within the bounds necessary to ensure an interior solution for all types $i \in I$ (see Appendix A for details), a drought will be declared if the marginal return to expected electoral success exceeds the cost:

$$\Phi\left(v_{cr}^{t-1} - \frac{1}{2} + L(\theta_{r'}, \zeta_{r'}) + \theta_r(d^t) + \zeta(v_{cr}^{t-1})\right) - \Phi\left(v_{cr}^{t-1} - \frac{1}{2} + L(\theta_{r'}, \zeta_{r'}) + \zeta(v_{cr}^{t-1})\right) \geq \eta^t, \tag{2}$$

where, again, $\Phi(.)$ is the cumulative density function of the shock ϵ. The party provides a declaration if the resulting positive shock to voter support increases the likelihood of winning by more than the marginal cost of providing the declaration, η^t. In each year, the government will rank constituencies by their marginal return to a declaration and provide a declaration to the N^t constituencies with the highest returns; therefore, η^t coincides with the marginal return to providing a declaration in the $N^t - th$ constituency. The likelihood of receiving a declaration then is increasing in the marginal return to a declaration.

Model Implications

In Appendix A, I provide proofs for the comparative statics I describe here.

Drought. Drought occurrence enters the model through its impact on the positive shift in support the ruling party receives from providing a declaration, $\theta_r(d^t)$. The marginal return to providing a declaration, as described by the left-hand side of Equation 2, is increasing in $\theta_r(d^t)$.

Proposition 1: The likelihood of receiving a declaration is higher if a drought has occurred.

Voters' utility is increasing and concave in consumption, so the drought-affected have a higher marginal utility for relief which translates into a greater increase in support for the ruling party. In a given constituency, drought then increases the marginal return to a declaration and therefore the likelihood of receiving a declaration.

Electoral Competition. The ruling party's allocation decision is a function of the existing support of the constituency, measured as the party's prior-election vote share v_{cr}^{t-1}. However, Indian state elections usually have more than two parties so the vote share is not a sufficient statistic in empirical specifications for determining: (1) whether the ruling party won the last

[27] This is a simplification of the actual process as the amount of money provided as relief varies across blocks.

election and (2) the margin of victory or loss. For this reason, I restate the following results in terms of the ruling party's prior-election vote margin, m as

$$m_{ct}^{t-1} = v_{cr}^{t-1} - (1 - v_{cr}^{t-1}) = 2(v_{cr}^{t-1} - \frac{1}{2}). \tag{3}$$

With this in mind, I consider how the marginal return to a drought declaration, and therefore declaration likelihood, varies in the prior-election vote margin. As shown in Appendix A, the marginal return to a drought declaration is maximized for a constituency with a baseline vote margin $\bar{m}(d^t) = -[\theta_r(d^t) + 2L(\theta_{r'}, \zeta_{r'}) + 2\zeta(v_{cr}^{t-1})]$. At this margin, the positive shift in support from a declaration makes the ruling party equally likely to win or lose the following election.[28] On the other hand, a constituency with a larger margin, $m^{'} > \bar{m}$, is already more likely to reelect the ruling party without a declaration while a constituency with a smaller margin, $m^{''} < \bar{m}$, is not expected to reelect the ruling party even with a declaration.

Appendix Figure A.1 illustrates how the marginal return to a drought declaration varies in the prior-election vote margin for the case of drought and no drought in a simplified setting that abstracts from incumbency effects and prior declaration effects ($\bar{m} = -\theta_r(d^t)$).[29] The return-maximizing vote margin $\bar{m}$ is marked by vertical lines and the marginal cost of a drought declaration η^t is shown by a horizontal line. The ruling party will allocate drought declarations to constituencies with vote margins for which the marginal return to a drought declaration curve falls above this horizontal line. Appendix Figure A.2 then illustrates a similar scenario but now allowing for an incumbency effect. As shown in the figure, an incumbency advantage results in a negative discontinuity in the return to a declaration between non-aligned and aligned areas while an incumbency disadvantage results in a positive discontinuity; again, this is because an incumbency advantage (disadvantage) means the ruling party is already more (less) likely to be reelected in aligned areas and therefore the value to providing relief is lower (higher) (see Proposition 3, below). Even with the inclusion of an incumbency effect, on average, the marginal return to a drought declaration and, therefore, the likelihood of receiving a drought declaration will be increasing in electoral competition (i.e., vote margins closer to 0).[30]

Proposition 2: The likelihood of receiving a declaration is decreasing in the prior-election vote margin for aligned constituencies and increasing for non-aligned constituencies.

[28]Relaxing the restriction that the mean of ϵ, μ, is zero, the return-maximizing vote margin becomes $\bar{m}(d^t) = -[\mu + \theta_r(d^t) + 2L(\theta_{r'}, \zeta_{r'}) + 2\zeta(v_{cr}^{t-1})]$.

[29]The model-generated relationship between the marginal return to a drought declaration and the ruling party's vote margin closely resembles the comparable empirical relationship between the average likelihood of a drought declaration and the average ruling party vote margin (see Figure 3).

[30]While the figures illustrate this relationship for example parameter values, this effect holds for parameters within the bounds assumed in the model.

In other words, the marginal return to a declaration is increasing in electoral competition for the ruling party and so declaration likelihood is higher in electorally competitive areas. Allowing for prior shifts in support due to incumbency and declarations, this relationship between the marginal return to a declaration and the *observed* prior-election vote margin m_{cr}^{t-1} continues to hold. However, the ruling party will now consider the *adjusted* vote margin $m_{cr}^{t-1} + L(\theta_{r'}, \zeta_{r'})$ when assessing the marginal return to a drought declaration. Appendix A provides the details of how the relationship between the vote margin and marginal return to a declaration is affected by a prior shift in support due to an incumbency effect (Appendix Figure A.3) or a declaration (Appendix Figure A.4).

The degree to which not accounting for these two prior shifts in support would bias empirical estimates of the likelihood of receiving a declaration for a given vote margin depends on a number of constituency-specific factors (see Appendix A). However, to give a concrete example, I consider the scenario depicted in Appendix Figure A.4 that imposes the simplifying assumptions that there are no prior incumbency effects and drought does not affect voter response to declarations ($\theta_r(1) = \theta_r(0)$). Additionally, I assume that the constituencies with the most competitive *observed* margins ($|m_{cr}^{t-1}| < .1$) received a declaration in the prior period, in line with the above predictions of the model. Then, regressing the indicator for whether a constituency received a declaration on the adjusted vote margin ($v_{cr}^{t-1} + L(\theta_{r'}, \zeta_{r'})$) in this scenario results in a coefficient that is four times larger than that estimated when not accounting for the bias. I return to the issue of this bias in the discussion of empirical specifications, which follows.

Ruling-Party Incumbency. The model allows for a ruling-party incumbency advantage/disadvantage, which generates a specific asymmetry in the relationship between the marginal return to a declaration and the ruling party's vote margin, as shown in Appendix Figure A.2.

Proposition 3: An incumbency advantage (disadvantage) causes a negative (positive) discontinuity in the marginal return to a declaration at a vote margin of 0.

An incumbency advantage implies that the ruling party's vote share will be 2ζ higher for a small increase in the vote margin (from a margin of 0) relative to a symmetric decrease in the margin. Therefore, the marginal return to allocating a drought declaration in constituencies where the ruling party won is discontinuously lower relative to those where it lost. As described in Appendix A, this discontinuity will result in a discontinuity in the likelihood of receiving a declaration as long as there are cases in which the marginal cost η^t is high enough that non-aligned areas are favored with declarations over aligned areas even at margins close to 0.

4 Empirical Strategy

According to the model, declaration likelihood should depend on drought (Proposition 1) and electoral competition for the ruling party (Proposition 2); further, there will be a discontinuity in declaration likelihood at a vote margin of 0, between non-aligned and aligned blocks, if a ruling-party incumbency effect exists (Proposition 3). I first focus on estimating the effects of drought and competition before turning to a specification used to identify a possible discontinuity in the likelihood of receiving drought relief.

I estimate the likelihood of a drought being declared in a block b located in constituency(ies) $c(b)$ and state $s(b)$ in year t utilizing the linear probability model specification

$$Declaration_{bt} = \alpha_{s(b)t} + \beta_0 drought_{bt} + \beta_1 |margin_{c(b)e(t)}| + \epsilon_{bt} \tag{4}$$

where $Declaration$ is an indicator for receiving a declaration; $drought$ is an indicator for a significant deviation in the June-September or June/July rainfall from its long-term average in year t; and $|margin|$ is the absolute value of the ruling party's vote margin in the prior election $e(t)$, a measure of electoral competition.[31] While I do not observe the marginal cost of a declaration (η^t in Equation 2), the state-year interacted fixed effects $\alpha_{s(b)t}$ remove variation in state-level budgets which, according to the model, determines this marginal cost.[32]

According to Proposition 1, drought should increase the likelihood of a drought declaration, $\beta_0 > 0$. The identifying assumption for the coefficient β_0 is that drought is exogenously determined relative to any omitted factors correlated with declarations. Defining drought as a negative rainfall shock, the assumption likely holds.[33]

Proposition 2 indicates that declaration likelihood should be decreasing in the absolute value of the ruling party's vote margin (increasing in electoral competition), $\beta_1 < 0$. However, Equation 4 will not causally identify this relationship (i.e., β_1) because it omits unobserved block-specific characteristics that impact both declaration likelihood and electoral outcomes. For example, the share of a block devoted to agriculture will determine its eligibility for declarations and likely represents a meaningful division in voters' interests (e.g., rural versus non-rural voters) which will be reflected in electoral outcomes (e.g., competitiveness). To account for such unobserved block-specific factors, in a second specification I add block fixed effects, α_b. The

[31] This is a linear approximation to the relationship between declaration likelihood and electoral competition suggested in the model; I also show results using a quadratic in the ruling party's vote margin as regressors.

[32] I treat Telangana and Andhra Pradesh as separate states for the entire sample.

[33] The assumption might not hold using hydrological indices to define drought, for example, as political factors could jointly determine dam releases of water and declaration allocations.

model in Section 3 identifies another bias in the above regression: the ruling party's current declaration decisions are influenced by prior-election-cycle declarations through their effect on $margin_{c(b)e(t)}$. The omission of past declarations in the fixed-effects specification violates the identifying assumption of sequential exogeneity. Therefore, I develop an instrument for the ruling party's vote margin meant to be uncorrelated with prior-election-cycle declarations.[34]

Finally, according to Proposition 3, if an incumbency effect exists then declaration likelihood will vary discontinuously at a margin of 0. I estimate a local linear regression

$$\begin{aligned} Declaration_{bt} =& \alpha_{s(b)t} + \delta aligned_{c(b)e(t)} + \phi_0 drought_{bt} + \phi_1 margin_{c(b)e(t)} \\ &+ \phi_2 margin_{c(b)e(t)} \times aligned_{c(b)e(t)} + \mu_{bt}, \end{aligned} \tag{5}$$

which tests for this discontinuity δ allowing for separate linear trends on either side of the cutoff $margin = 0$.[35] If an incumbency advantage exists, aligned areas are already more likely to reelect the ruling party and so less likely to receive a declaration, $\delta < 0$. Again the omission of block-specific factors will confound the interpretation of δ; therefore, I will also use a regression discontinuity design (RDD), an approach meant to control for such unobserved factors when testing for a discontinuity.

4.1 Instrument Construction for the Ruling Party's Vote Margin

According to the model, electoral outcomes in election $e(t)$ will be affected by the declarations that occur in the the prior election cycle; therefore, an exogenous instrument for the ruling party's vote margin in election $e(t)$ should not correlate with declarations made between elections $e-1$ and e. I start by constructing an instrument for the two components of the vote margin, the vote share of the ruling party and that of the main opposition party, for each election (2008/9, 2013/14, and 2018/19). To construct instruments for the counterfactual vote shares that would exist in the absence of changes caused by past declarations, I calculate the interaction of the party's 2004 vote share in the constituency with the state-level change in support between 2004 and the relevant election.[36] The cross-sectional variation from the 2004 election occurs prior to both the 'confounding' declarations and a re-drawing of constituency boundaries and therefore could not have been influenced by these declarations (for details on

[34] Another way to resolve this issue would be to directly control for past declarations, but I only observe past declarations for a limited portion of the panel. See Imai and Kim (2019) for more details on identification in dynamic models using unit fixed effects.

[35] The non-linear relationship between declaration likelihood and electoral competition (see Figure 3) causes bias in the (full bandwidth) linear approximation and so I also report results for a 4^{th} order polynomial.

[36] This instrument largely follows that proposed by Shaukat (2019).

mapping of constituencies, see Appendix B).[37] The state-level leave-one-out change in support excludes the constituency-specific shifts in political support correlated with these declarations.

For each party p and constituency c, I estimate the 2004 vote share over all overlapping 2004 constituencies $m \in M$ as

$$voteshare^{p}_{c,2004} = \frac{1}{M}\sum_{m=1}^{M} voteshare^{p}_{m,2004}.$$

Again, the purpose of this vote share is to generate an estimate for the support for each party that would exist in the absence of changes in political support due to a prior-election-cycle declaration; however, some of the ruling and opposition parties in the post-2007 elections did not exist in 2004 while others did not run widely.[38] In such cases, I assign the average of 2004 vote shares for the observed ruling/opposition parties, or a vote share of .36 (see Appendix B for robustness checks using the 25^{th} or 75^{th} percentile).[39] I measure the change in state-level support for each party p between 2004 and the given election e as

$$\Delta^{e}_{2004} voteshare^{p}_{s(c)-c} = 1 + \left(voteshare^{p}_{s(c)-c,e} - \frac{1}{M}\sum_{m=1}^{M} voteshare^{p}_{s(m)-m,2004} \right),$$

where the first term is the election e vote share in state $s(c)$, excluding voting results in constituency c, and the second term is the comparable leave-one-out state-level vote share for the party in 2004, averaged over the 2004-constituency(ies) $m \in M$ which map to constituency c.[40]

Finally, I estimate the predicted vote share for the ruling party r and the opposition party o in each constituency-election as

$$\widetilde{voteshare}^{p}_{ce} = voteshare^{p}_{c,2004} \times \Delta^{e}_{2004} voteshare^{p}_{s(c)-c}$$

to construct the ruling party's vote margin,

$$\widetilde{margin}_{ce} = \widetilde{voteshare}^{r}_{ce} - \widetilde{voteshare}^{o}_{ce}.$$[41]

[37]Post-2007 declarations are allocated based on electoral outcomes in 2008-constituency boundaries but the instrument relies on cross-sectional variation in historical political support for the 2004-constituency boundaries. Iyer and Reddy (2013) finds that partisan politics did not strongly influence changes in constituency boundaries.

[38]The YSR Congress Party (YSRCP) split from the India National Congress (INC) in Andhra Pradesh (first election in 2014) and the Karnataka Janata Paksha and Badavara Shramikara Raitara Congress Party split (only for the 2013 election) from the BJP in Karnataka ("BJP's merger and acquisitions gave it the edge in many seats", 2018). In these cases, I use information for the existing party.

[39]The mean vote share for the ruling and opposition parties in the elections $e(t)$, the values for which the instrument is constructed, is .46.

[40]Specifically, $voteshare^{p}_{s(c)-c,e} = (votes^{p}_{s(c),e} - votes^{p}_{c,e})/(votes_{s(c),e} - votes_{c,e})$, where, again, I estimate separate state-level shifts for Telangana and Andhra Pradesh in all elections.

Using this instrument in Equation 4, the identifying assumption is as follows: conditional on drought occurrence and block- and state-year-specific factors, the constructed vote margin for all elections up to $e(t)$ in constituency(ies) $c(b)$ must not correlate with omitted factors that influence declarations in block b and period t (sequential exogeneity). This assumption is plausible as the variation in the instrument is driven by cross-sectional and temporal variation in support for the ruling and opposition parties that is not impacted by local time-varying factors (i.e., prior-election-cycle declarations). However, two main threats to identification remain. First, it is possible that the 2004 vote shares correlate with the 2004 vote margin which in turn impacts declarations allocated between 2004 and 2008/9 (i.e., the 'confounding' declarations for the 2008/9 election). Second, if an event is widespread or has local spillover effects, it may still influence the measured change in support for each party despite the leave-one-out structure. In the following section, I address these concerns along with potential violations of the exclusion restriction.

5 Empirical Results

I first test whether drought occurrence and electoral competition increase declaration likelihood (Propositions 1 and 2). Panel A of Table 2 provides estimates of Equation 4, where the dependent variable is the indicator for receiving a drought declaration. Column 1 controls only for state-year interacted fixed effects while columns 2 and 3 additionally control for block fixed effects. Comparing the results in columns 1 and 2, failing to control for unobserved block-specific characteristics generates significant bias in estimating the effect of electoral competition on declaration likelihood. However, as described previously, the fixed-effects OLS specification still does not provide a causal estimate of this relationship because the impact of prior-election-cycle declarations on electoral competition violates the sequential exogeneity assumption needed for identification. By instrumenting for the ruling party's vote margin, column 3 provides a causal estimate of the effect of electoral competition on declaration likelihood.[42] The coefficient in the IV specification is significantly larger in magnitude than that of the OLS; this result is consistent with the example described in Section 3 which suggests that the bias from not adjusting the vote margin for past declarations alone can result in a four times smaller coefficient on the absolute value of the vote margin. Therefore, if anything, not accounting for the effect of prior-election-cycle declarations biases against finding the result predicted by Proposition 2.

[42]As shown in Panel B of Table 2, the instrumented vote margin has a positive, significant effect on the observed vote margin and appears to be a strong predictor with a first-stage F-statistic of 15.

Consistent with Proposition 1, drought occurrence increases the likelihood of a declaration by about 18 percentage points, a 56 percent increase relative to a mean declaration likelihood of 33 percent. In line with Proposition 2, the coefficient on the absolute value of the ruling party's vote margin is $-.909$ (s.e. .302); therefore, a one standard deviation decrease in the absolute value of the ruling party's vote margin (.10), an increase in competition, increases declaration likelihood by 9 percentage points.[43]

To test for a discontinuity in declaration likelihood between aligned and non-aligned blocks (Proposition 3), Table 3 provides estimates of Equation 5. The OLS specification results in an estimated discontinuity of $-.028$ (s.e. .012) (column 1).[44] However, the omission of block-specific characteristics is likely to bias the estimation of the discontinuity. The close election RDD specification overcomes this issue under the assumption that relevant unobserved block-specific characteristics are similar across blocks in which the ruling party lost or won by a small margin. The coefficient for the discontinuity in the RDD specification is $-.111$ (s.e. .012) (column 2).[45] Therefore, alignment to the ruling party reduces declaration likelihood, consistent with the ruling party allocating declarations in response to an incumbency advantage.

Using the test proposed in McCrary (2008), I find a discontinuity in the distribution of the ruling party's vote margin at 0 (.389, s.e. .093), suggesting that the ruling party is more likely than the opposition to win a close election.[46] This discontinuity in the vote margin at 0 is only an issue for identification if it is generated by the manipulation of elections. State elections in India are administered by an independent organization, the Election Commission of India, making this type of manipulation less likely. Further, recent work suggests that this discontinuity may arise even in the absence of the strategic sorting, or manipulation of elections, that would bias the RDD estimate (Snyder et al., 2015).

5.1 Instrument Robustness

In the following sections, I consider robustness checks of the IV result for electoral competition.

[43]I also consider an alternative functional form for these specifications, replacing the absolute value of the ruling party's vote margin with a quadratic function of the ruling party's vote margin. Again the results indicate that declaration likelihood is increasing in electoral competition (see Appendix Table C.2).

[44]Replacing the linear approximation on either side of the cutoff at a margin of 0 with 4^{th} order polynomials results in an estimated discontinuity of $-.046$ (s.e. .024) (illustrated in Appendix Figure C.1).

[45]The RDD specification utilizes an optimal bandwidth of .039 and a triangular kernel, with robust standard errors clustered by block (optimal bandwidth estimation based on Calonico et al. (2020)).

[46]Appendix Figure C.1 provides plots of the distribution of the running variable, which demonstrate the discontinuity estimated by the McCrary test. Note, this test is performed at the constituency-election level.

5.1.1 Alternative Instrument Constructions

The instrument for the vote margin should be as-good-as random relative to the question, does increased electoral competition for the ruling party increase the likelihood of a declaration? As stated in Section 4.1, one concern is that the leave-one-out state-level change in support for each party might still be impacted by factors local to a block b (declarations) if those factors impact nearby areas. In Table 4, I expand the leave-out to the entire district (column 2) and to all blocks with centroids within 100 kilometers of the centroid of block b (column 3). If the impact of past declarations on political support was widespread, I'd expect the expansion of the leave-out to affect the results; however, adjusting the leave-out in each case does not significantly impact the results. Finally, it is possible that the 2004 vote shares used to construct the instrument for the vote margin correlate with the 2004 ruling party's vote margin, which determines official drought declarations in the election cycle that precedes the 2008/9 election. To determine whether this is an issue, I reconstruct the instrument using baseline vote shares from the 1999 election interacted with the state-level, leave-one-out change in support for each party between 1999 and election $e(t)$ (see column 4). Again, though the coefficient on the absolute value of the vote margin is smaller, it is not significantly different from the baseline results. In conclusion, I interpret these findings as strong support for the as-good-as random assignment of the instrument; therefore, in the remaining robustness sections I focus on potential violations of the exclusion restriction.

5.1.2 Additional Criteria in the National Guidelines

In a study of a formula-based public program in England, Ward and John (1999) suggest that even when the rules are followed political influence may enter the formula itself. For example, urban areas are not eligible for drought declarations and political influence in the 2004 state governments, captured by the instrument, may have impacted which blocks were designated as urban. I remove all blocks in Hyderabad and much of Bangalore from the baseline sample, but I am unable to identify which of the remaining blocks are designated as urban by the states. For this reason, column 2 of Table 5 instead removes blocks whose average night lights in 2008 are above the 95^{th} percentile and therefore might be considered urban. Removing these blocks does not have a significant impact on the results, suggesting potential correlation between the instrument and designations as urban is not a concern. In the remaining columns, I focus on testing whether potential correlation between the instrument and additional environmental criteria can explain the paper's findings. Column 3 adds indicators for the occurrence of a dry spell (4 consecutive weeks of reduced rainfall) and prior-year drought as well as the ratio of rainfall to its long-term average and its squared term for June-September and June/July. Columns 4 through 7 then build on this specification, adding the NDVI (vegetation index) for the nine 16-day periods that overlap June-September, the monthly mean soil moisture for June-September, district-level groundwater for May and August (for available district-years), and the district-level ratio of current crop area sown to average crop area sown over the period (available for the years 2008 to 2018), respectively. Adding additional rainfall measures does cause a statistically significant reduction in the magnitude of the coefficient on the vote margin; interestingly, this suggests that variation in electoral competition across election cycles correlates with temporal variation in the severity of local rainfall shocks, even after removing 'drought-proneness' with block fixed effects. However, the coefficient then remains stable when including additional environmental variables. Further, the finding that electoral competition increases declaration likelihood holds and is statistically significant across all specifications.

5.1.3 Additional Political Measures

The instrument for the ruling party's vote margin might also correlate with other electoral outcomes that influence the likelihood of receiving drought relief, violating the exclusion restriction. For example, the instrument for competition for the ruling party might correlate with overall competitiveness; Shaukat (2019) finds evidence of positive candidate selection (in terms of education) in competitive elections in India, which might indicate those candidates are more effective in obtaining drought declarations. The instrument may also correlate with voter turnout and the ruling party might target relief to areas where voters are more politically active. To address these concerns, Table 6 repeats the estimation of Equation 4 adding the Herfindahl-Hirschman Index (HHI) of vote shares, including realized vote shares for the ruling and opposition party, (column 2) and voter turnout (column 3). The magnitude of the coefficient on the ruling party's vote margin is not significantly changed in either specification; therefore, a violation of the exclusion restriction due to the correlation of the instrument with other electoral outcomes is unlikely.

6 The Impact of Drought and Drought Declarations on Local Development

In the preceding sections, I showed that declarations break with national guidelines and that this mistargeting is partly driven by the political motives of the state ruling party. However, whether this distortion of declaration allocations represents a misallocation of public resources is an open question. Prior work on the political manipulation of public resources focuses on structurally estimating the welfare impacts of political distortions (Azulai, 2017; Finan & Mazzocco, 2020). In this section, I take an alternative approach towards answering this question by evaluating the impact of declarations on local economic development in drought-affected and non-drought-affected blocks. I estimate the impact of declarations on local agricultural production, a primary sector in rural economies.

This leads to the following specification for studying the impacts of drought and declarations,

$$\begin{aligned} IHS(\Delta NDVI_{bt}) =& \alpha_b + \alpha_{s(b)t} + \delta_0 Rain_{bt} + \delta_1 Rain_{bt}^2 + \beta_0 drought_{bt-1} \\ &+ \beta_1 Declaration_{bt-1} + \beta_2 drought_{bt-1} \times Declaration_{bt-1} + \epsilon_{bt}, \end{aligned} \tag{6}$$

where the dependent variables is the inverse-hyperbolic sine (IHS)[47] of the NDVI-based proxy for agricultural production.[48] The independent variables of interest are the indicators for drought and receiving a declaration, as well as their interaction, in the prior year $t-1$.[49] The specification also includes block and state-year interacted fixed effects. I add a quadratic in the ratio of June-September rainfall to its long-term-average in year t to control for (negative) correlation in rainfall shocks across years.[50] The coefficient β_1 measures the effect of a prior-year declaration on local development; while one might expect the coefficient to be positive, it is not necessarily true that public programs lead to a rise in agricultural production. For example, Asher and Novosad (2020) finds no impact of India's rural roads program on this measure. The coefficient β_2 estimates the differential effect of receiving a declaration in drought-affected areas; a positive coefficient would then suggest that drought declarations are more effective when appropriately targeted. These coefficients will reflect causal estimates if there is no omitted factor that correlates with declarations and drought while also influencing agricultural production, conditional on controls for contemporaneous rainfall shocks and block and state-year fixed effects.

[47] The inverse hyperbolic sine transformation is similar to the log transformation and so I interpret the results of this regression in the same way as a log-linear regressions.

[48] Asher and Novosad (2020) uses this difference between the maximum and early-season values of the vegetation index as a proxy and shows that it correlates with agricultural production (and other measures likely correlated with agricultural production). I regress the IHS of agricultural production (in tonnes) for crop-district-year observations on the IHS of the average NDVI difference for blocks in a district, controlling for district and year FE as well as crop indicators. I find that a 10 percent increase in the average NDVI difference for blocks in a district is correlated with 2.3 percent higher district-level crop production (coef. .233, s.e. .016).

[49] The earliest drought declarations are made in August, after the agricultural season; further, in Andhra Pradesh and Telangana, during this period less than half of blocks received a declaration by October and 15 percent did not receive a declaration until the following calendar year. Therefore, impacts on agricultural production can only occur in the following year.

[50] I use a second order polynomial in the rainfall *ratio*, instead of contemporaneous rainfall, because it measures deviations from the block-specific *normal* rainfall. As well as acting as controls, the coefficients δ_0 and δ_1 on the rainfall ratio variables measure how agricultural production responds to local rainfall shocks.

Column 1 of Table 7 displays the results of an estimation of Equation 6 when only block and state-year fixed effects are included. The block fixed effects remove potentially important variation in time-invariant local characteristics that likely correlate with declarations and explain agricultural production (e.g., aridity, soil type, cropping patterns). State-year fixed effects likewise account for relevant unobserved variation, including changes in state-level public programs. First, as one might expect, the proxy for agricultural production is concave in contemporaneous normalized rainfall, suggesting that crop growth is reduced by local extreme rainfall shocks. The coefficient on the declaration indicator on the other hand is positive and statistically significant, as is the coefficient on the interaction between the declaration and drought indicators. A prior-year drought declaration is associated with a 6 percent increase in agricultural production in non-drought affected areas but an 11 percent increase in drought-affected areas. This increase in agricultural production associated with a prior-year declaration can be considered significant in magnitude compared to the null effect for a village gaining access to a rural road, for example (Asher & Novosad, 2020). Further, the more positive correlation between a prior declaration and agricultural production in drought-affected areas suggests that declarations might be more effective when well-targeted.

When controlling for a quadratic in the contemporaneous rainfall ratio, a prior-year drought has no direct effect on agricultural production (column 1). Since agricultural production is largely driven by contemporaneous monsoon rainfall, it is perhaps not surprising that a prior-year drought has no effect when accounting for the temporal correlation in rainfall shocks. However, to further control for potential changes in the agricultural environment following a drought, column 2 of Table 7 adds contemporaneous mean monthly soil moisture and a quadratic in the ratio of June/July rainfall to its long-term-average. The coefficient on declarations decreases slightly from .063 (s.e. .009) to .058 (s.e. .009) and the coefficient on the interaction increases from .040 (s.e. .011) to .052 (s.e. .011).

6.1 Identification Concerns in Estimating Declaration Effects

A clear threat to identification is the possibility of other public programs, not encompassed by the comprehensive drought relief program, that correlate with the allocation of drought relief and influence agricultural production. In the preceding sections of this paper, I consider a number of empirical specifications to convincingly identify the political manipulation of declarations. It is also plausible that other public programs are allocated based on political motivations and therefore correlate with drought relief. To determine whether this is an issue, it is necessary to test the results when only using variation in declaration allocations that is likely to be uncorrelated with such programs. Unfortunately, the instrument I construct in Section 4.1 is meant to capture exactly this variation in political motivations that likely correlates with such programs. Therefore, I consider two alternative approaches to addressing this concern.

First, in column 3 of Table 7, I add a series of political variables to control for possible political incentives that drive allocations of both declarations and unobserved programs.[51] As shown, the addition of these controls results in almost no change in the coefficients on the declaration and interaction variables; further, the addition of political controls does not meaningfully affect the explanatory power of the specification. Given these results, it is unlikely that unobserved programs explain the positive effect of prior-year declarations on agricultural production.

Second, drought occurrence meaningfully determines declarations and is unlikely to correlate with possibly confounding unobserved programs that are not part of the overarching relief program, making it a *relevant* instrument. The main deterrent to using it as an instrument then is a failure of the exclusion restriction: prior-year drought has a direct impact on agricultural production or affects production through some other unobserved factor. Column 2 of Table 7 suggests that a prior-year drought does not directly affect agricultural production once controlling for fixed effects and contemporaneous environmental factors; therefore, in Appendix Table C.4, I repeat the estimation of the specification in column 2 of Table 7 as an IV regression using prior-year drought as the excluded instrument for a prior-year declaration. Setting aside other possible failures of the exclusion restriction, this robustness check confirms the positive effect of prior-year declarations on agriculture.

6.2 Potential Mechanisms for Targeting Effects

The findings above show that the positive correlation between prior-year declarations and the proxy for agricultural production is higher for well-targeted declarations (e.g., declarations targeted to drought-affected blocks). If declarations are less effective in non-drought-affected blocks, then allocating declarations to non-drought-affected blocks instead of drought-affected blocks represents a misallocation of public resources; this variation in effectiveness due to targeting could be caused by drought relief being better suited to, or better implemented in, drought-affected areas or drought-affected households utilizing the relief in a different manner. However, in this section I consider alternative explanations, other than differential effectiveness,

[51] The political variables include the absolute value of the ruling party's vote margin; the aligned indicator; a comparable indicator for alignment to the federal ruling coalition; voter turnout; the HHI of vote shares; the number of candidates who ran; and controls for the political party of the MLA(s).

for the observed variation due to targeting.

The amount of relief associated with a declaration should vary based on the amount of land/-households affected (according to guidelines), which might in turn be determined by drought severity. If well-targeted declarations are associated with increased funding, this could explain the increased positive association with agricultural production; in other words, the observed greater increase in agricultural production associated with a prior-year declaration in drought-affected blocks is driven by more relief, not increased effectiveness. While I only have access to data for one state in one year, this data is for the first set of declarations following India's transition to a rules-based system; therefore, these planned relief expenditures for Karnataka in 2018 likely represent 'an upper bound' for appropriately allocated relief based on the extent of drought's impact (GoK, 2018). While I find that the amount of planned expenditures correlates with a block's geographic area, a proxy for exposed land/households, there is no significant correlation with drought occurrence or severity (see Appendix Table C.6).

It is possible that a prior-year drought impacts households' desired cropping choices and relief enables households to make these changes; if affected households switch to crops with higher NDVI difference values, the stronger correlation between well-targeted prior-year declarations and the NDVI-based proxy might reflect changed cropping patterns instead of increased agricultural production. Block-level cropping data is not available, so I instead add controls for the share of agricultural land devoted to specific crops at the district level (for details, see Appendix B). As shown in Appendix Table C.5, the addition of these controls results in almost no change in the coefficients, suggesting this is not a concern.

Finally, the correlation between a prior-year declaration and agricultural production might depend on rainfall received during the current agricultural season. For example, we might expect that prior-year declarations have no effect in areas with drought because drought-induced crop failure outweighs any possible positive impacts of relief. If this is the case, the increased correlation between well-targeted prior-year declarations and agricultural production might be partially explained by the negative correlation in drought between year t and $t-1$. Column 4 of Table 7 allows the effect of prior-year declarations to vary in the current rainfall ratio but the coefficient on the interaction of the prior-year drought and declaration indicators is nearly unaffected, suggesting this is not an issue.

6.3 Assessing the Misallocation of Declarations

After demonstrating the robustness of the positive effect of prior-year declarations on agricultural production and excluding alternative explanations for the effects of targeting, I interpret the empirical results as strong evidence that: (1) relief is effective in improving agricultural production in the following year and (2) relief is more effective when appropriately targeted (adhering to the rainfall criteria of the national guidelines). Next, I consider whether the relief package associated with declarations has differential effects across the prior-year rainfall distribution, as opposed to only comparing drought-affected blocks to all other blocks. To do so, I replace the indicator for drought in Equation 6 with indicators for the quintiles of the prior-year ratio of June-September rainfall to its long-term average.

Figure 4 displays the change in agricultural production associated with a prior-year declaration for blocks within each quintile of the prior-year rainfall shock distribution (i.e., coefficient on declaration plus coefficient on declaration interacted with quintile dummy). The first quintile aligns closely with the indicator for drought-affected blocks (areas with less than 78 percent of normal rainfall compared to 75 percent for the indicator) while the third quintile consists of block-year observations with nearly normal rainfall (ratio of 1) and the fifth quintile contains block-years with excessive seasonal rainfall (more than 28 percent above normal). The effect of declarations on agricultural production displays a distinct u-shape across the prior-year normalized rainfall distribution, indicating that the increase in agricultural production following a declaration is largest in the tails of the distribution. The result that declarations are most effective in increasing agricultural production in drought-affected blocks holds, and is statistically significant, when now comparing drought-affected blocks to blocks in each of the other four quintiles separately.[52] There is also a statistically significant rise in production following a declaration in areas that experienced a more moderate negative rainfall shock (second quintile). Interestingly, declarations also result in a statistically significant rise in agricultural production in the right tail of the distribution (excessive rainfall). Therefore, declarations appear to improve agricultural production in areas impacted more generally by a negative environmental shock in the prior year. This suggests that providing aid to areas stricken by excessive rainfall may be an effective disaster relief strategy, though it is not suggested by the national guidelines for drought relief.[53] On the other hand, prior-year declarations have no significant effect on

[52] The ruling party might target relief to drought-affected areas where future agricultural returns are highest; however, this appears unlikely as the results are unchanged when controlling for prior-year environmental measures that the ruling party might use to differentiate drought-affected areas (see Appendix Figure C.2).

[53] It is possible that areas with right-tail rainfall shocks also received flood relief.

agricultural production in blocks where prior-year rainfall was normal or just above normal.

During the sample period, only 43 percent of all declarations go to block-year observations in the lowest quintile where the positive correlation with production is highest (30 to 54 percent across the three states) while 35 percent of block-year observations in the lowest quintile did not receive a declaration. On the other hand, 25 percent of all declarations go to block-year observations with rainfall in the third and fourth quintile, where there is no appreciable positive effect of declarations on production (18 to 33 percent across states). Based on these aggregate declaration counts, there was significant scope for reallocating declarations from blocks where the estimated effect on the proxy for agricultural production in the following year is 0 percent to blocks where the proxy for production might have increased by 10 percent; in other words, aggregate state-level production might have been increased by reallocating declarations according to guidelines. These results then suggest that the distortion of relief allocations, due to electoral incentives for example, is costly.[54]

7 Conclusion

In this paper, I study the allocation of drought relief in three states of southern India. I show that drought-affected areas are in fact more likely to receive drought relief. However, I also identify political distortions in the allocation of drought relief. I find that the state ruling party targets relief to areas where it faced higher electoral competition (won/lost by a smaller vote margin). On the other hand, political alignment (connections) with the state ruling party reduce the likelihood that an area receives relief; specifically, I estimate a negative discontinuity in the likelihood of receiving drought relief between non-aligned and aligned areas. I present a dynamic probabilistic voting model that explains these patterns of political manipulation. The model also points to omitted variable bias in empirical specifications relating the allocation of drought relief to these measures of electoral incentives. Therefore, I construct instruments for a party's vote share by interacting cross-sectional variation in historical vote shares with a leave-one-out change in support for the party at the state level. The predicted vote shares for the ruling party and its opposition then form an instrument for the ruling party's vote

[54] In Appendix Table C.7, I explore how drought relief might impact broader economic activity within blocks, using the IHS of night lights as the dependent variable (comparable to column 3 of Table 7). Columns 1 and 2 use the block's average and median light, respectively, and do not find a positive effect of relief. Column 3 utilizes the 5^{th} percentile of night lights within a block and the results appear more similar to those found for agricultural production; prior-year declarations are associated with 6 percent higher night lights, with no differential effect for drought-affected blocks. Overall the findings are consistent with, for example, the existence of a concave relationship between agricultural production and night lights.

margin, a measure of electoral competition. I utilize this instrument to validate the finding that states target electorally competitive areas with relief. To confirm a negative discontinuity in the likelihood of receiving a declaration between non-aligned and aligned areas (at a vote margin of 0), I utilize a regression discontinuity design.

This paper considers drought relief in southern India, a region frequently exposed to drought and where households are highly vulnerable to the negative impacts of drought. Importantly, the paper provides suggestive evidence that drought relief is effective in increasing agricultural production in the following year. The increase in agricultural production associated with drought relief is highest in areas that experienced severe drought; however, this correlation is also positive, and statistically significant, in areas that experienced moderate drought or excessive rainfall. On the other hand, there is no statistically significant effect for areas that experienced about normal or just above normal rainfall in the prior year. I consider a number of robustness checks to strengthen the argument that the above associations in fact represent the impact of receiving a drought relief on local agricultural production. Though suggestive, these results have important policy implications for India's disaster management programs. First, the recent changes in the national guidelines requiring strict adherence to rainfall criteria and allowing for drought relief both in the case of severe and moderate drought will lead to improved agricultural production. Second, providing relief for areas affected by excessive rainfall might also be an effective strategy for disaster relief.

The Indian government provided national guidelines in the 2009 Drought Manual for how states should allocate drought relief, based on environmental factors; however, the national government still allowed for politicians and state government officials to exercise discretion in drought relief decisions. This retained discretion at the state level led to a recent Supreme Court case which found that state governments were failing to provide drought relief to drought-affected areas. The court case also led to a fundamental shift in India's drought relief program from a discretionary policy with national guidelines to a rules-based program (Bera & Sen, 2016). It may still be too early to tell whether the court's ruling and updated policy will have a meaningful effect on the allocation of drought relief. This paper, however, provides evidence that state governments target drought relief based on political motives even while citing adherence to national guidelines. An additional policy implication then is that rules-based policies may not be sufficient in ensuring programs reach their intended beneficiaries, even when those rules are externally-set; instead, a rules-based policy combined with a credible threat of monitoring and enforcement may be needed to achieve the intended targeting of public programs.

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8 Tables and Figures

Table 1: Summary Statistics for Block-Year Observations

Statistic	N	Mean	St. Dev.	Min	Max
$Declaration_{bt}$	14,043	0.330	0.470	0	1
$drought_{bt}$	14,043	0.177	0.382	0	1
$margin_{c(b)e(t)}$	14,043	0.011	0.147	−0.553	0.711
$\|margin_{c(b)e(t)}\|$	14,043	0.105	0.104	0.0001	0.711
$aligned_{c(b)e(t)}$	14,043	0.566	0.496	0	1

Note: This table reports summary statistics for block-year observations of the dependent and independent variables used in the primary specifications of this paper. Declaration is an indicator that a block b received an official drought declaration in year t while drought is an indicator that the block experienced sufficiently below-average June/July or June-September rainfall. The variable margin is the ruling party's vote margin in the block's constituency(ies) $c(b)$ for the election $e(t)$ which precedes year t while aligned is an indicator that the margin was positive, or that the ruling party won the election.

Table 2: Drought Declarations and Electoral Competition

	(1)	(2)	(3)
Panel A:		$Declaration_{bt}$	
$drought_{bt}$	0.245***	0.191***	0.184***
	(0.009)	(0.007)	(0.008)
$\lvert margin_{c(b)e(t)} \rvert$	0.028	−0.190***	−0.909***
	(0.046)	(0.032)	(0.302)
Observations	14,043	14,043	14,043
Panel B:			$\lvert margin_{c(b)e(t)} \rvert$
$\lvert \widetilde{margin}_{c(b)e(t)} \rvert$			0.148***
			(0.038)
$drought_{bt}$			−0.009***
			(0.002)
Observations			14,043
R^2			0.582
First Stage F-Stat			15
Specification	OLS	OLS	IV
Block FE	No	Yes	Yes
State-Year FE	Yes	Yes	Yes

Note: Panel A of this table reports estimation of Equation 4, where the indicator for block b receiving a drought declaration in year t is regressed on the absolute value of the ruling party's vote margin and an indicator for drought occurrence controlling for state-year fixed effects (OLS specification in column 1) and adding block fixed effects (OLS specification in column 2 and IV specification in column 3). Panel B reports the results of the first stage, using the instrument for the ruling party's vote margin described in Section 4.1. The Kleibergen-Paap Wald rk F statistic is reported. The Anderson-Rubin Wald test has a p-value of 0.0000. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Drought Declarations and Ruling-Party Incumbency Effects

	$Declaration_{bt}$	
	(1)	(2)
$aligned_{c(b)e(t)}$	-0.028^{**}	-0.111^{***}
	(0.012)	(0.012)
Observations	14,043	3,959
Specification	OLS	RDD
drought	Yes	Yes
State-Year FE	Yes	Yes

Note: This table reports estimation of Equation 5, where the indicator for block b receiving a drought declaration in year t is regressed on the indicator for alignment to the ruling party, allowing for separate linear trends in the ruling party's vote margin on either side of the cutoff at a margin of 0. Controls include an indicator for drought occurrence and state-year interacted fixed effects. Column 1 reports the OLS estimation with standard errors clustered by block. Columns 2 reports a regression discontinuity design (RDD) specification using an optimal bandwidth of .039 and a triangular kernel, with robust standard errors (optimal bandwidth estimation based on Calonico et al. (2020)). The table reports the *effective* number of observations for the RDD specification. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Robustness to Instrument Construction

	Baseline Instrument	District Leave-Out	100 Kilometer Leave-Out	1999 Election Vote Shares
	(1)	(2)	(3)	(4)
Panel A:		$Declaration_{bt}$		
$drought_{bt}$	0.184^{***}	0.185^{***}	0.184^{***}	0.186^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
$\lvert margin_{c(b)e(t)}\rvert$	-0.909^{***}	-0.882^{***}	-0.897^{***}	-0.730^{**}
	(0.302)	(0.294)	(0.301)	(0.332)
Panel B:		$\lvert margin_{c(b)e(t)}\rvert$		
$\lvert \widehat{margin}_{c(b)e(t)}\rvert$	0.148^{***}	0.149^{***}	0.147^{***}	0.158^{***}
	(0.038)	(0.038)	(0.038)	(0.045)
$drought_{bt}$	-0.009^{***}	-0.009^{***}	-0.009^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	14,043	14,043	14,043	14,043
R^2	0.582	0.582	0.582	0.582
First Stage F-Stat	15	15	15	12
Block FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Note: Panel A of this table reports IV estimations of Equation 4, where the indicator for block b receiving a drought declaration in year t is regressed on the absolute value of the ruling party's vote margin and an indicator for drought occurrence. Panel B reports the first stage regression for each IV specification. All specifications include block and state-year fixed effects. Column 1 repeats the estimation with the baseline instrument; column 2 increases the leave-out in the shift factor to exclude the votes for the whole district in which block b is located; column 3 instead increases the leave-out in the shift factor to exclude the votes for all constituencies whose centroid falls within 100 kilometers of the centroid of constituency $c(b)$; and column 4 replaces the 2004 baseline vote shares with 1999 vote shares. The Kleibergen-Paap Wald rk F statistic for the endogenous variable is reported. The Anderson-Rubin Wald test has a p-value of 0.0000 in columns 1 through 3 and 0.0033 in column 4. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Robustness to Additional Controls for National Guidelines

		Excluding:	Additional Controls for:				
	Baseline Specification	Urban Blocks	Continuous Rainfall	Normalized Diff. Vegetation Index	Soil Moisture	Groundwater Level	Crop Area Sown
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:				$Declaration_{bt}$			
$drought_{bt}$	0.184***	0.186***	0.012	0.003	0.005	0.006	0.006
	(0.008)	(0.008)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
$\lvert margin_{c(b)e(t)}\rvert$	−0.909***	−0.918***	−0.734***	−0.741***	−0.737***	−0.719***	−0.766**
	(0.302)	(0.290)	(0.271)	(0.268)	(0.267)	(0.278)	(0.321)
Panel B:				$\lvert margin_{c(b)e(t)}\rvert$			
$\lvert\widehat{margin}_{c(b)e(t)}\rvert$	0.148***	0.159***	0.146***	0.145***	0.144***	0.142***	0.137***
	(0.038)	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)	(0.043)
$drought_{bt}$	−0.009***	−0.009***	−0.002	−0.002	−0.003	−0.002	−0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	14,043	13,503	14,043	14,043	14,043	13,871	12,587
First Stage F-Stat	15	16	14	14	14	14	10
Block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Panel A of this table reports IV estimations of Equation 4, where the indicator for block b receiving a drought declaration in year t is regressed on the absolute value of the ruling party's vote margin and an indicator for drought occurrence. Panel B reports the first stage regression for each IV specification. Column 1 reports the specification with baseline controls: block and state-year fixed effects. Column 2 removes all blocks likely to be considered urban, or whose average night lights in 2008 is above the 95^{th} percentile. Each consecutive column then adds additional environmental controls to the baseline specification: a quadratic in the rainfall ratios for June-September, a quadratic in the rainfall ratio for June/July, an indicator for a 4-week dry spell, and an indicator for a prior-year drought (column 3); the normalized difference vegetation index for each of nine 16-day periods overlapping June-September (column 4); mean monthly soil moisture for June through September (column 5); the district-level groundwater level in May and August (column 6); and district-level ratio of crop area sown in year t to the average crop area sown for 2008 to 2018 (column 7). The Kleibergen-Paap Wald rk F statistic for the endogenous variable is reported. The Anderson-Rubin Wald test has a p-value of 0.0000 in columns 1 through 2, .0008 in column 3, .0010 in column 4, .0009 in column 5, 0.0014 in column 6, and .0029 in column 7. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Robustness to Additional Political Variables

	(1)	(2)	(3)
Panel A:		$Declaration_{bt}$	
$drought_{bt}$	0.184***	0.184***	0.184***
	(0.008)	(0.008)	(0.008)
$\lvert margin_{c(b)e(t)} \rvert$	−0.909***	−0.953***	−0.878***
	(0.302)	(0.345)	(0.293)
$HHI_{c(b)e(t)}$		0.020	
		(0.017)	
$turnout_{c(b)e(t)}$			0.107
			(0.099)
Panel B:		$\lvert margin_{c(b)e(t)} \rvert$	
$\lvert \widehat{margin}_{c(b)e(t)} \rvert$	0.148***	0.133***	0.152***
	(0.038)	(0.038)	(0.039)
$drought_{bt}$	−0.009***	−0.008***	−0.009***
	(0.002)	(0.002)	(0.002)
$HHI_{c(b)e(t)}$		0.045***	
		(0.004)	
$turnout_{c(b)e(t)}$			0.102
			(0.075)
Observations	14,043	14,043	14,040
R^2	0.582	0.606	0.582
First Stage F-Stat	15	12	15
Block FE	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes

Note: Panel A of this table reports IV estimations of Equation 4, where the indicator for block b receiving a drought declaration in year t is regressed on the absolute value of the ruling party's vote margin and an indicator for drought occurrence. Panel B reports the first stage regression for each IV specification. Column 1 reports the specification with baseline controls: block and state-year fixed effects. Column 2 adds the Herfindahl-Hirschman Index (HHI) of (endogenous) vote shares while column 3 adds voter turnout. The Kleibergen-Paap Wald rk F statistic for the endogenous variable is reported. The Anderson-Rubin Wald test has a p-value of 0.0000 in columns 1 and 3 and 0.0001 in column 2. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

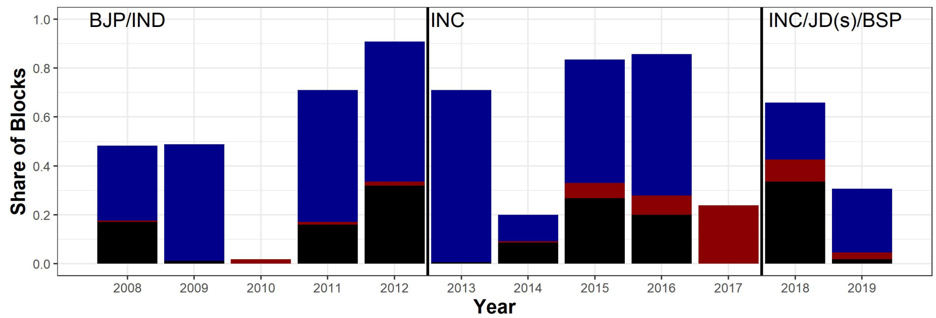
Table 7: Impact of Drought and Declarations on Agricultural Production

	$IHS(\Delta NDVI_{bt})$			
	(1)	(2)	(3)	(4)
$Rain_{bt}$	0.452***	0.193***	0.200***	0.092**
	(0.055)	(0.050)	(0.050)	(0.047)
$Rain^2_{bt}$	−0.122***	−0.029	−0.033*	−0.006
	(0.023)	(0.019)	(0.019)	(0.018)
$drought_{bt-1}$	0.012	0.003	0.004	0.003
	(0.009)	(0.009)	(0.009)	(0.009)
$Declaration_{bt-1}$	0.063***	0.058***	0.058***	−0.259***
	(0.009)	(0.009)	(0.009)	(0.074)
$drought_{bt-1} \times Declaration_{bt-1}$	0.040***	0.052***	0.050***	0.053***
	(0.011)	(0.011)	(0.011)	(0.011)
$Rain_{bt} \times Declaration_{bt-1}$				0.454***
				(0.114)
$Rain^2_{bt} \times Declaration_{bt-1}$				−0.145***
				(0.044)
Observations	14,037	14,037	14,034	14,034
R^2	0.752	0.764	0.766	0.767
Block FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Env. Variables	No	Yes	Yes	Yes
Political Variables	No	Yes	Yes	Yes

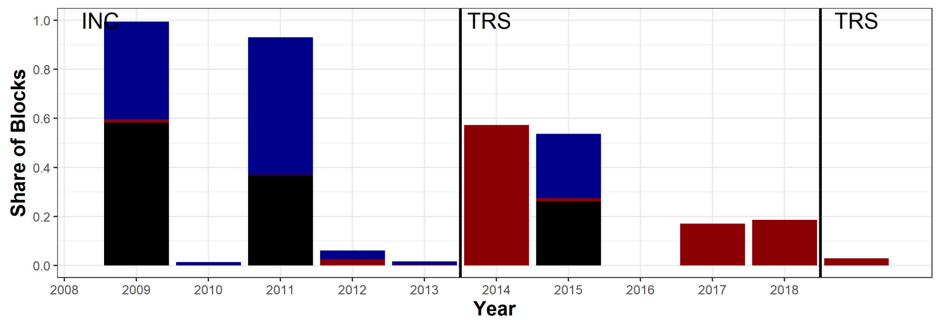
Note: This table reports estimations of Equation 6 where the dependent variable is the inverse-hyperbolic sine (IHS) of the NDVI difference, or the difference between maximum and early-season vegetation index, for block b in year t. The independent variables are the ratio of current June-September rainfall to its long-term average (*Rain*) in block b and year t, an indicator for drought occurrence in year $t-1$, and an indicator for receiving an official drought declaration in year $t-1$. Column 1 reports the specification with block and state-year fixed effects. Column 2 adds controls for mean monthly soil moisture and the June/July rainfall to its long-term-average (and the squared ratio). Column 3 adds controls for the absolute value of the ruling party's vote margin; the indicator for being aligned to the state ruling party; a comparable indicator for alignment to the federal ruling coalition; voter turnout; the HHI of vote shares; the number of candidates who ran; and indicators for the political party of the MLA(s). Column 4 incorporates interaction terms between the declaration indicator and quadratic in the contemporanous June-September rainfall ratio. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: Variation in Drought and Drought Declarations Across Election Cycles

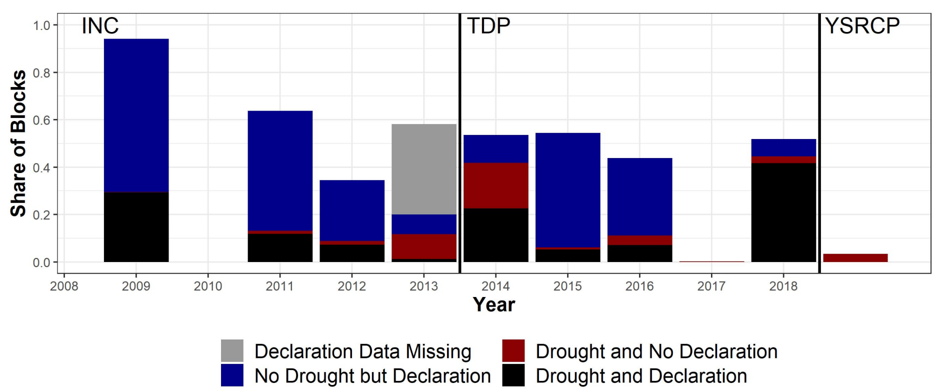
(a) Karnataka



(b) Telangana



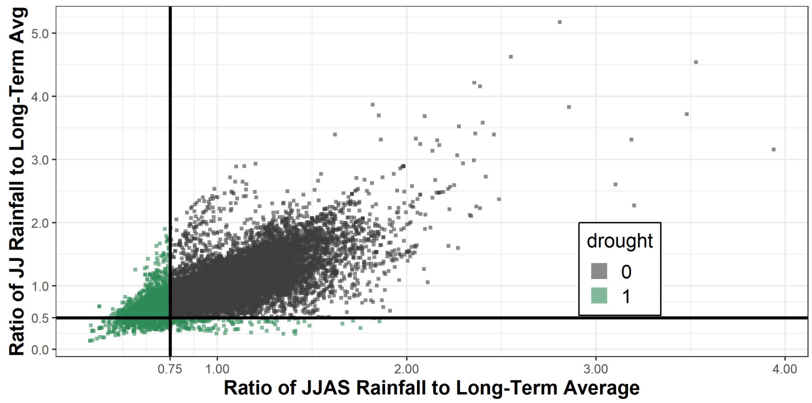
(c) Andhra Pradesh



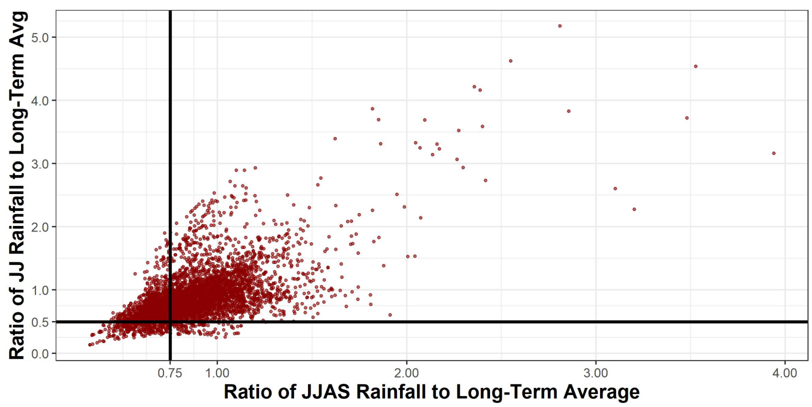
Note: This figure plots the share of blocks in each year that had a declaration and drought (black); declaration but no drought (blue); drought but no declaration (red); and declaration data missing (grey). The omitted share is blocks with no drought and no declaration. The indicator for drought is defined in Section 2.1. The tables also display the separate election cycles: 2008-2013, 2014-2017, and 2018 for Karnataka and 2009-2013, 2014-2018, and 2019 for Andhra Pradesh/Telangana. The ruling coalitions in Karnataka were Bharatiya Janata Party (BJP)/Independents (IND), India National Congress (INC), and INC/Janata Dal (Secular) (JD(S))/Bahujan Samaj Party (BSP), respectively. In Andhra Pradesh and Telangana INC was the ruling party followed by Telugu Desam Party (TDP) and Telangana Rashtra Samithi (TRS), respectively; in the most recent election, the YSR Congress Party (YSRCP) came to power in Andhra Pradesh while TRS maintained control of Telangana.

Figure 2: Variation in Drought and Declarations by Rainfall Shocks

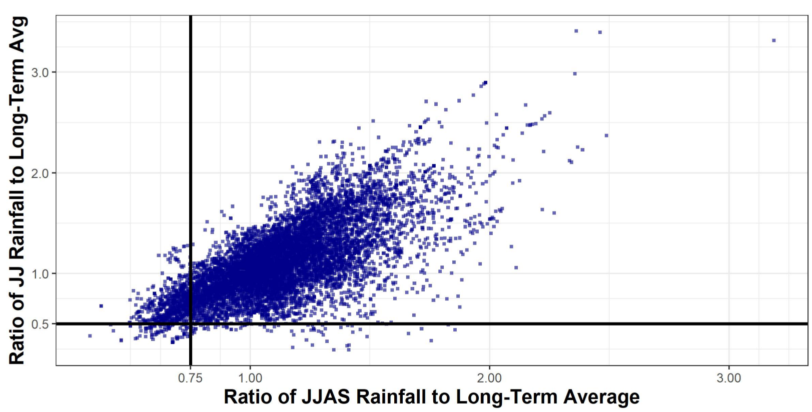
(a) Drought-Affected Blocks



(b) Drought Declared Blocks

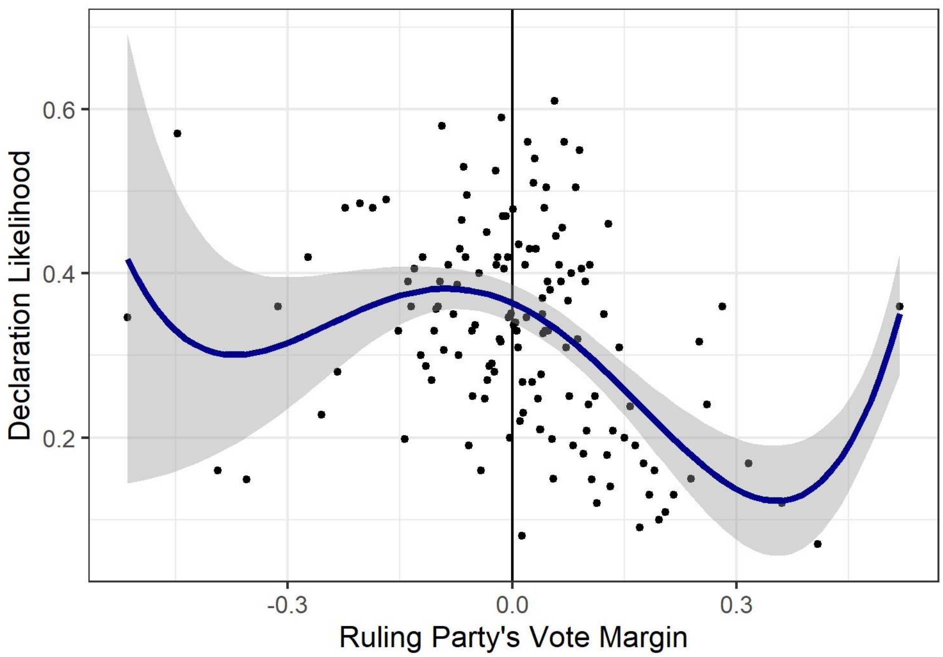


(c) Non-Declared Blocks



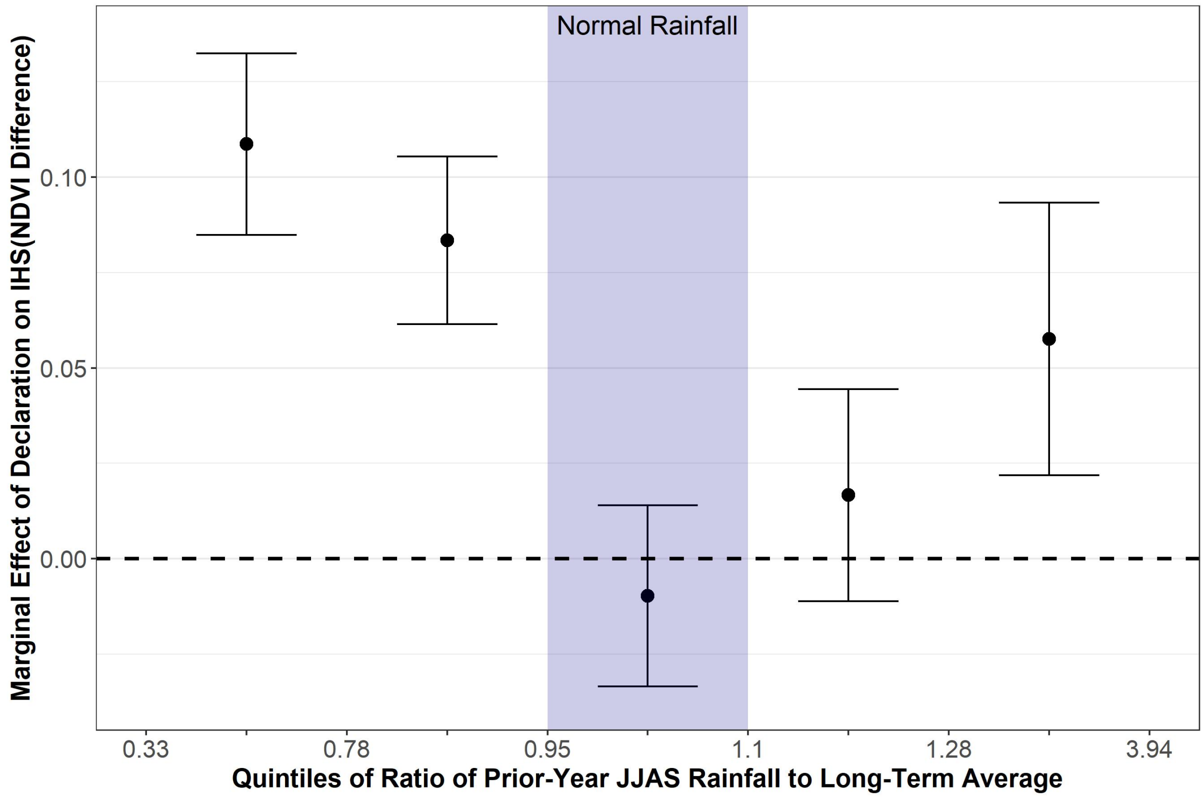
Note: This figure contains a series of scatter plots where the x-axis is the ratio of June-September rainfall to its long-term average (full-season local rainfall shocks) and the y-axis is the ratio of June/July rainfall to its long-term average (early-season local rainfall shocks). Panel A displays the points which meet rainfall criteria outlined in the national guidelines (and therefore are defined as drought-affected in this paper) in green while points not meeting the criteria are grey; the points in green meet either the criteria that the June-September rainfall ratio is below .75 (vertical black line) or that the June/July rainfall ratio is below .5 (horizontal black line). Panel B then contains only block-year observations where a drought declaration was received while Panel C contains only block-year observations where a declaration was not received. The figures highlight the difference between observations eligible for drought declarations according to the (primary) rainfall criteria provided in the guidelines, Panel A, relative to those that do or do not receive declarations, Panels B and C.

Figure 3: Binscatter of Drought Declaration Likelihood Against Ruling Party's Vote Margin



Note: Each point in this figure compares the average likelihood of receiving an official drought declaration for all observations in a bin (y-axis) to the average ruling party's vote margin for all observations in the bin (each bin contains about 100 block-year observations). The curve then represents a regression of the average declaration likelihood on a fourth order polynomial in the average vote margin (with confidence intervals shaded).

Figure 4: Impact of Declarations on Agricultural Production by Prior-Year Rainfall



Note: This figure plots coefficient estimates and confidence intervals for an estimation of Equation 6 where the dependent variable is the inverse-hyperbolic sine (IHS) of the NDVI difference, or the difference between maximum and early-season vegetation index, for block b in year t and the indicator for drought has been replaced by indicators for the quintile of the prior-year rainfall shock distribution. The rainfall shock is measured as the ratio of June-September rainfall in the prior-year to its long-term-average. The figure displays the coefficient estimates for the declaration indicator interacted with quintile of the prior-year rainfall distribution and the x-axis provides the range of prior-year rainfall shock values for each quintile. The lowest quintile then displays the impact of declarations in areas affected by a negative rainfall shock (less than 78% of normal rainfall) while the highest quintile contains areas with excessive rainfall (more than 28% above normal). The third quintile represents areas with rainfall around the average (about a ratio of 1). Controls include block and state-year interacted fixed effects; mean monthly soil moisture; the June-September rainfall to its long-term-average (and the squared ratio); the June/July rainfall to its long-term-average (and the squared ratio); the absolute value of the ruling party's vote margin; the indicator for being aligned to the state ruling party; a comparable indicator for alignment to the federal ruling coalition; voter turnout; the HHI of vote shares; the number of candidates who ran; indicators for years since the last election; and indicators for the political party of the MLA(s). Standard errors are clustered at the block level.

Appendix A Solving the Model For Drought Declaration Allocations

A.1 Generalizing Voters' Preferences to Governing Period t

During the first governing period $t = 1$, the ruling party makes declaration allocations knowing the vote share in the second election will be

$$v_{cr}^2 = \sum_i \beta_{ic} Pr(\sigma_{ir}^2 > 0).$$

The probability of a voter of type i voting for the ruling party candidate in a given governing period t is

$$Pr(\sigma_{ir}^{t+1} > 0) = \begin{cases} 0 & \sum_{s=0}^{t+1} \epsilon_{cr}^s + \theta_r(d_c^t) r_c^t + \zeta(v_{cr}^{t-1}) < -v_{cr}^0 \\ 1 & \sum_{s=0}^{t+1} \epsilon_{cr}^s + \theta_r(d_c^t) r_c^t + \zeta(v_{cr}^{t-1}) > 1 - v_{cr}^0 \\ v_{cr}^0 + \sum_{s=0}^{t+1} \epsilon_{cr}^s + \theta_r(d_c^t) r_c^t + \zeta(v_{cr}^{t-1}) & otherwise. \end{cases}$$

In all periods, I assume that the combined effect of the external shocks ϵ and temporary shifts $\theta_r(\cdot)$ and $\zeta(\cdot)$ is within the bounds necessary to avoid a corner solution (the third case above). With this assumption, the probability of a voter of type i voting for the ruling party in the election that follows the first governing period is

$$Pr(\sigma_{ir}^2 > 0) = \frac{1}{2} + \frac{\bar{\varphi}_{ir}}{\delta_i} + \theta_r(d_c^1) r_c^1 + \zeta(v_{cr}^0) + \epsilon_{cr}^2.$$

and the second election vote share can be rewritten as

$$v_{cr}^2 = v_{cr}^0 + \theta_r(d_c^1) r_c^1 + \zeta(v_{cr}^0) + \epsilon_{cr}^2.$$

In the absence of declarations ($r_c^1 = 0$) and an incumbency advantage/disadvantage ($\zeta(v_{cr}^0) = 0$), the expected vote share in the second election is simply the vote share in the prior election.

Because the changes in support due to declarations and ruling-party incumbency only last one period while the common shock to voter preferences ϵ_{cr}^t is permanent, after the second election occurs we have $\sigma_{ir}^3 = \varphi_{ir} + \delta_i \epsilon_{cr}^2$ in governing period $t = 3$. Therefore, for any governing period $t \in \{1, 3, 5, ...\}$, σ_{ir} can be thought of as voter i's updated baseline support for the current ruling party r and can be written as

$$\sigma_{ir}^t = \varphi_{ir} + \delta_i \sum_{s=0}^{t} \epsilon_{cr}^s$$

with $\epsilon_{cr}^0 = 0$ and, again, $\epsilon_{cr}^t = 0$ for $t \in \{1, 3, 5, ...\}$. Then, generalizing to any governing period $t \in \{1, 3, 5, ...\}$ the probability of a voter of type i voting for the ruling party in the following election is

$$Pr(\sigma_{ir}^{t+1} > 0) = \frac{1}{2} + \frac{\bar{\varphi}_{ir}}{\delta_i} + \sum_{s=0}^{t} \epsilon_{cr}^s + \theta_r(d_c^t) r_c^t + \zeta(v_{cr}^{t-1}) + \epsilon_{cr}^{t+1}$$

and the vote share for the ruling party is

$$v_{cr}^{t+1} = v_{cr}^0 + \sum_{s=0}^{t} \epsilon_{cr}^s + \theta_r(d_c^t) r_c^t + \zeta(v_{cr}^{t-1}) + \epsilon_{cr}^{t+1}.$$

Iterating the right-hand-side of the above equation forward, I find

$$v_{cr}^{t+1} = v_{cr}^{t-1} + L(\theta_{r'}, \zeta_{r'}) + \theta_r(d_c^t) r_c^t + \zeta(v_{cr}^{t-1}) + \epsilon_c^{t+1},$$

where $r^{'}$ was the ruling party during the governing period in $t-2$. The function L accounts for the impact of temporary shifts in support for the ruling party due to incumbency and declarations,

$$L(\theta_{r'}, \zeta_{r'}) = [\theta_{r'}(d_c^{t-2}) r_c^{t-2} + \zeta(v_{cr'}^{t-3})] \times \left[\mathbf{1}\{r \neq r^{'}\} - \mathbf{1}\{r = r^{'}\}\right].$$

Because the transitory shift in voters' preferences due to prior declarations and incumbency is relative to the ruling party r', the above equation adjusts for a past positive shift for the ruling party $r^{'}$ having increased (decreased) the vote share v_{cr}^{t-1} if the ruling party is the same (different) in governing period t.

A.2 Solving the Ruling Party's Allocation Decision

Imposing that ϵ is within the bounds defining the third case of the above equation for all types $i \in I$ and $\epsilon \sim \Phi(0, \nu^2)$, the decision rule for the ruling party is

$$\Phi\left(v_{cr}^{t-1} - \frac{1}{2} + L(\theta_{r'}, \zeta_{r'}) + \theta_r(d^t) + \zeta(v_{cr}^{t-1})\right) - \Phi\left(v_{cr}^{t-1} - \frac{1}{2} + L(\theta_{r'}, \zeta_{r'}) + \zeta(v_{cr}^{t-1})\right) \geq \eta^t,$$

The ruling party compares the difference in the likelihood of winning the upcoming election with a declaration to the likelihood of winning in the absence of a declaration to determine whether the resulting change in expected electoral success exceeds the marginal cost of a declaration. As described in Section 3, I will restate the above equation in terms of the ruling party's vote margin, instead of vote share, and impose that ϵ is distributed normally. The decision rule can be rewritten as

$$\int_{\frac{1}{2}m_{rc}^{t-1} + L(\theta_{r'}, \zeta_{r'}) + \zeta(v_{cr}^{t-1})}^{\frac{1}{2}m_{rc}^{t-1} + L(\theta_{r'}, \zeta_{r'}) + \theta_r(d^t) + \zeta(v_{cr}^{t-1})} \frac{1}{\sqrt{2\pi\nu^2}} \exp\{-\frac{\epsilon^2}{2\nu^2}\} d\epsilon > \eta^t.$$

In the remaining sections, I consider comparative statics for this decision rule.

A.2.1 Parameter for Voter Response to Declarations and Drought

I first consider the affect of marginal changes in the parameter value $\theta_r(d^t)$ on the return to a drought declaration. Taking the derivative of the decision rule with respect to $\theta_r(d^t)$, we find

$$\frac{1}{\sqrt{2\pi\nu^2}} \exp\{-\frac{(\frac{1}{2}m_{rc}^{t-1} + L(\theta_{r'}, \zeta_{r'}) + \theta_r(d^t) + \zeta(v_{cr}^{t-1}))^2}{2\nu^2}\} > 0,$$

so that the marginal return is increasing in the size of the positive preference shift due to a declaration. The assumptions that drought is a negative wealth shock and voters have increasing and concave utility results in voters' marginal utility from a declaration being greater when a drought has occurred. As stated previously, I then allow this increased marginal utility for drought-affected voters to translate into a more positive shift in preferences for the ruling party, or $\theta_r(1) > \theta_r(0)$. This combined with the above result suggests that the marginal return to a drought declaration is higher for drought-affected areas. Further, because the ruling party will provide declarations to the constituencies with a marginal return above the marginal cost η_t, this indicates that declaration likelihood will be higher in drought-affected areas.

A.2.2 Ruling Party's Vote Margin

The ruling party's vote margin in the election that precedes the governing period is a strong signal for how the ruling party will perform in the next election. Taking the derivative of the marginal return to a declaration with respect to the vote margin results in the equation

$$\frac{1}{2\sqrt{2\pi\nu^2}} \Bigg(\exp\{-\frac{(\frac{1}{2}m_{rc}^{t-1} + L(\theta_{r'}, \zeta_{r'}) + \theta_r(d^t) + \zeta(v_{cr}^{t-1}))^2}{2\nu^2}\} \\ - \exp\{-\frac{(\frac{1}{2}m_{rc}^{t-1} + L(\theta_{r'}, \zeta_{r'}) + \zeta(v_{cr}^{t-1}))^2}{2\nu^2}\} \Bigg).$$

This derivative equals 0 at a vote margin $\bar{m} = -[\theta_r(d^t) + 2L(\theta_{r'}, \zeta_{r'}) + 2\zeta(v_{cr}^{t-1})]$, which is the return-maximizing vote margin for allocating a declaration. Because the marginal return to providing a declaration is single-peaked, the return to allocating a declaration is declining for vote margins larger than or smaller than the return-maximizing margin. In turn, this suggests that the likelihood of receiving a drought declaration is also declining for increasingly higher, or lower, vote margins.

According to the model $\theta_r > 0$ and so imposing no incumbency advantage/disadvantage ($\zeta = 0$) and no lagged declaration impacts, the return-maximizing vote margin will occur at a negative prior vote margin, $\bar{m} = \theta_r(d^t) < 0$. This simplified scenario is shown in Figure A.1 in the case that a drought occurs and the case in which no drought occurs in t. In this scenario, for a given magnitude of the vote margin, $|m_{cr}^{t-1}|$, the return to allocating a declaration will be higher in non-aligned constituencies where $m_{cr}^{t-1} < 0$. Also, as long as the the return maximizing vote margin, or the shift in support due to a declaration, is not too large, the return to a declaration will be decreasing in the absolute value of the ruling party's prior vote margin (a linear approximation to the relationship shown in the figure). The model imposes that the shift in support is in fact less than 10 percent.

A.2.3 Incumbency Advantage/Disadvantage

The most decisive impact of the incumbency effect is the discontinuity it creates in the marginal return to a declaration at a vote margin of 0. As shown above in the equation for the ruling party's decision rule, the probability of winning the election in $t+1$ changes discontinuously at 0 due to the fact that in places previously won ($m_{cr}^{t-1} > 0$) support for the ruling party is increased by ζ while in places previously lost ($m_{cr}^{t-1} < 0$) support is decreased by ζ (with $\zeta > 0$ representing an incumbency advantage). This results in a discontinuity in the marginal return to a declaration, as shown in Figure A.2, that is negative (positive) moving from aligned to non-aligned constituencies in the case of an incumbency advantage (disadvantage) relative to a smooth curve in the case of no incumbency effect. Another way to visualize this discontinuity, as shown in Figure A.2, an incumbency advantage (disadvantage) takes the baseline curve for the marginal return to a declaration and shifts it towards (away from) a vote margin of 0 *separately* for aligned and non-aligned constituencies.

Also shown in the figure, identifying this discontinuity in the marginal return to a drought declaration may not be possible using the empirically observable declaration likelihood. For the scenarios shown in the figure, a constituency with a vote margin close to 0 will receive a declaration if it is aligned or non-aligned (because the ruling party targets competitive constituencies). Therefore, the discontinuity will only be estimated in empirical specifications if there are situations where the marginal cost η^t is high enough that aligned areas are favored over non-aligned areas (or vice-versa) even when elections are close; such a scenario can be seen in the figure if we consider a ruling incumbency advantage (e.g., $zeta = .1$) depicted with a green dashed line and a marginal cost $\eta^t > .12$, so a horizontal line just above the blue dotted line in the figure.

Figure A.2 also shows how the return-maximizing vote margin varies with an incumbency disadvantage, incumbency advantage, and no incumbency effect. Comparing an incumbency advantage to the results with no incumbency effect, the return-maximizing vote margin will occur for a more negative number $-[\theta_r(d^t) + 2\zeta]$ in aligned constituencies and a less negative number $-[\theta_r(d^t) - 2\zeta]$ (or positive number if $2\zeta > \theta_r$) in non-aligned constituencies. An incumbency disadvantage would have the opposite effect. Again, assuming the incumbency effect is not too large in magnitude, the marginal return to a drought declaration will increase in electoral competition. The figure also displays the marginal cost of providing a declaration, η^t, which the ruling party considers in its decision rule; again, η^t represents the marginal cost in the N^{th} constituency and so it will shift depending upon the shift in the marginal return to a declaration caused by the incumbency effect.

In the remaining section, I impose an incumbency advantage and consider the impact of prior declarations and prior incumbency advantage on the relationship between the marginal return to a drought declaration and the ruling party's vote margin.

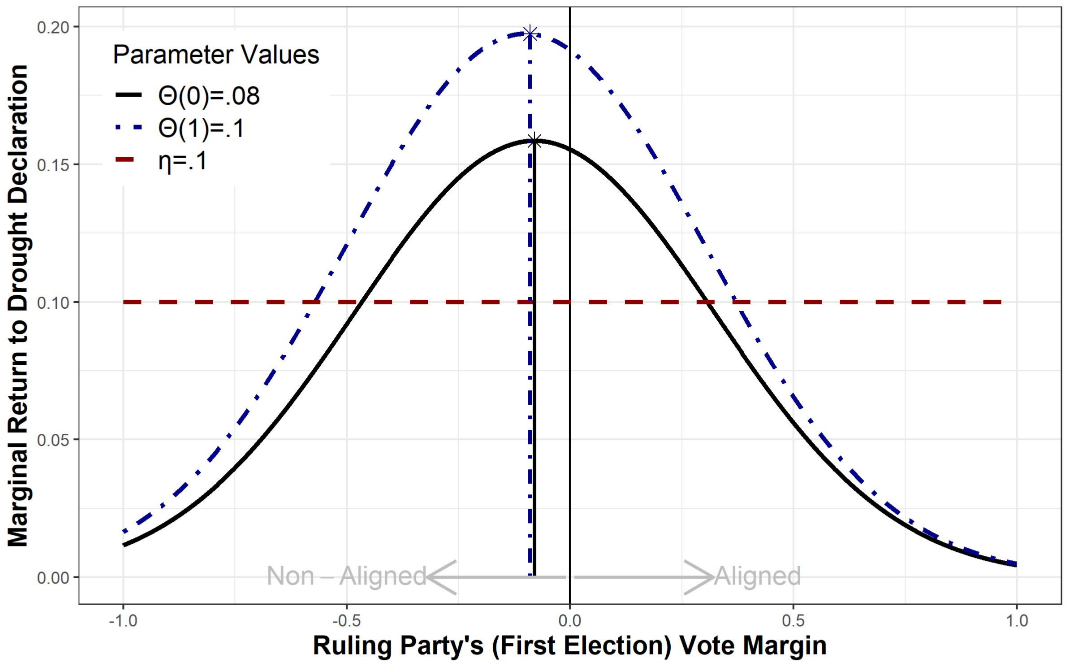
A.2.4 Accounting for Prior Incumbency Effects

As shown in the equation for the ruling party's decision rule above, the prior incumbency effects shift the value of the marginal return over the distribution of the vote margin and therefore the return-maximizing vote margin for the ruling party, $\bar{m} = -[\theta_r(d^t) + 2L(\theta_{r'}, \zeta_{r'}) + 2\zeta(v_{cr}^{t-1})]$. An incumbency advantage following the election $t-3$ temporarily increased support for the then ruling party r' in election $t-1$ for aligned constituencies; therefore, to estimate support for the ruling party r in t the vote share/margin must be adjusted downward if $r = r'$ and upward otherwise (with opposite effects for non-aligned constituencies). While here I assume an incumbency advantage, in general the prior incumbency effect depends on: (1) whether an incumbency advantage or disadvantage exists, (2) the party identity of the ruling party in each period, and (3) whether the constituency was aligned after the $t-3$ election. These variations, however, can be collapsed into two cases: in some constituencies the ruling party r will have been benefited from the incumbency effect in election $t-1$ and in others the current ruling party was disadvantaged. Figure A.3 plots the ruling party's decision rule, for example parameter values, for the case where there is no prior incumbency effect and the cases where a constituency was advantaged or disadvantaged by a prior incumbency effect (assuming no prior declaration effect). As shown, the inclusion of prior incumbency effects shifts the return-maximizing vote margin along the distribution of prior ruling party vote margins. This prior-incumbency-induced shift reduces the marginal return to providing a declaration for some margins m_{cr}^{t-1} and increases it for others. Further, the prevailing marginal cost of a declaration η_t, shown in the figure, assumes all constituencies fall into one of the given cases and, given these parameter values, happens to be the same in each case. In reality, however, different constituencies will be either advantaged or disadvantaged by past incumbency effects and so the marginal cost η^t will depend on the observed marginal returns to a declaration in the observed constituencies.

A.2.5 Accounting for Prior Declaration Effects

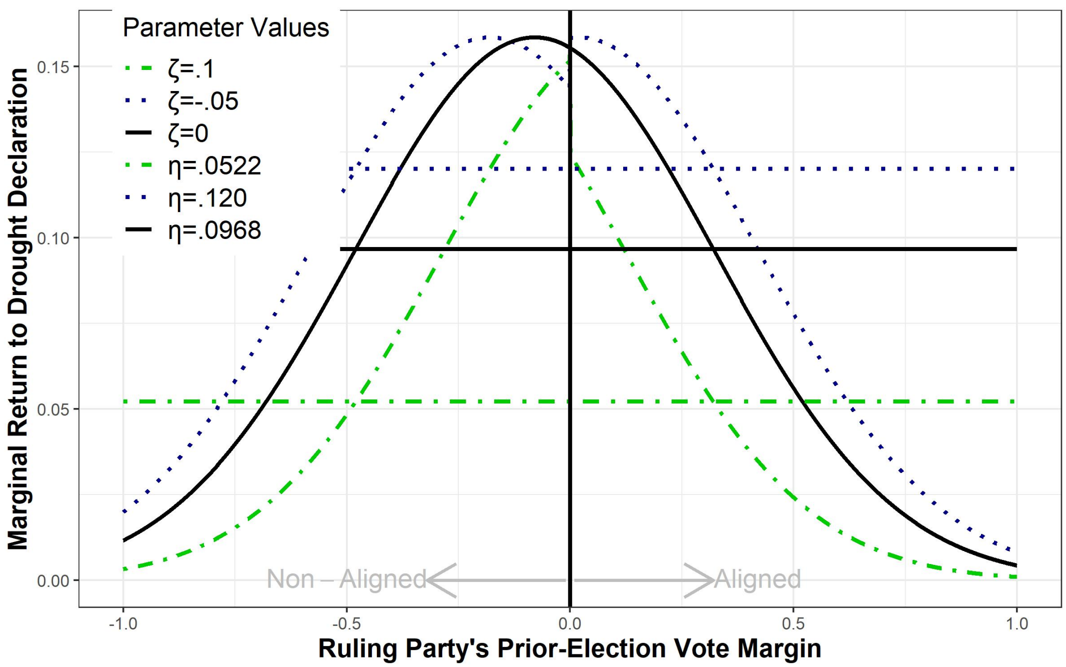
Next, I assume no prior incumbency effect and focus on the variation induced by prior declaration effects. The effect of a prior declaration depends of course on whether a constituency received a declaration and whether or not the ruling party is the same in both elections. A declaration in $t-2$ temporarily increased support for the ruling party r' relative to the opposition party in election $t-1$; and so, to assess support for the ruling party r in governing period t the vote share/margin needs to be adjusted downwards if $r = r'$ and upwards otherwise in constituencies that previously received a declaration. Figure A.4 plots the ruling party's decision rule for the case where there was no prior declaration and the cases where a prior declaration occurred and either advantaged or disadvantaged the current ruling party in election $t-1$ (imposing no prior incumbency effect). Again, the marginal cost to providing a declaration η^t assumes all constituencies fall into one of the 3 cases shown and happens to be the same marginal cost in each case for the given set of parameter values. However, the marginal cost will depend on the number of constituencies that did in fact receive a declaration in $t-2$ and whether it benefited or disadvantaged the ruling party r in election $t-1$.

Figure A.1: The Marginal Return to Drought Declaration by Ruling Party's Vote Margin



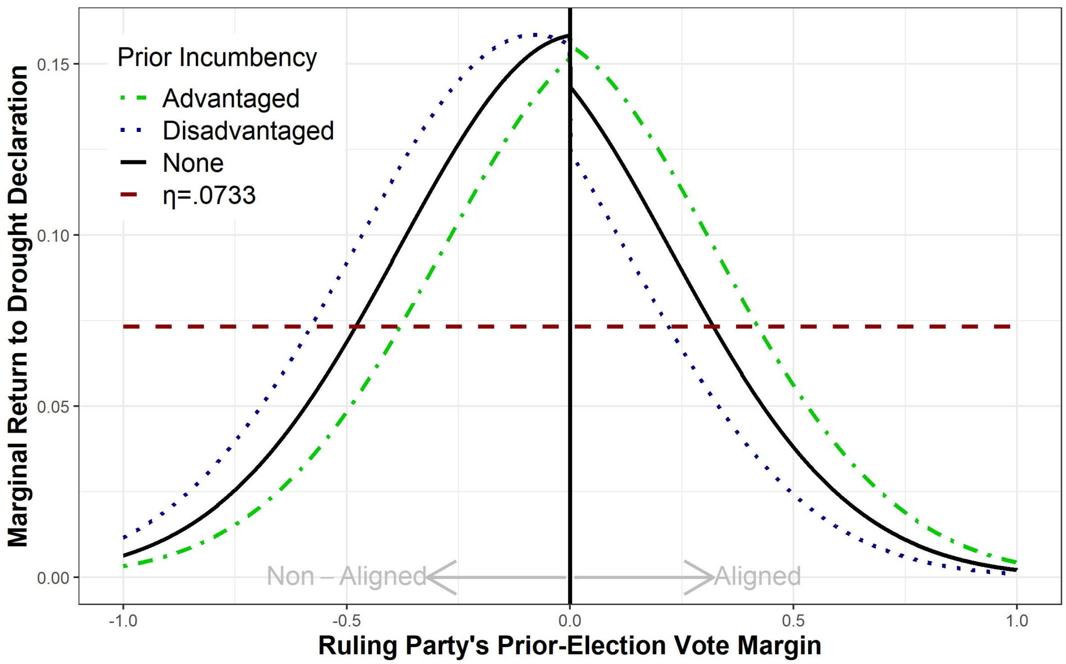
Note: This figure depicts the marginal return to a drought declaration and marginal cost to a declaration, as described in Equation 2, for different possible values of the ruling party's (first election) vote margin. For exposition, I fix $\epsilon_{cr} \sim N(0, .04)$. This figure assumes no incumbency effects and no shifts in support due to prior incumbency or prior declarations. The plot is split by a vertical line where the ruling party's vote margin is equal to zero: non-aligned constituencies fall to the left of the line while aligned constituencies fall to the right of the line. The figure plots the marginal return in the case where no drought has occurred ($\theta_r(0) = .08$, solid black line) and a drought has occurred ($\theta_r(1) = .1$, dashed blue line). The return-maximizing vote margin, $\bar{m}(d^t)$, in each case is highlighted by a vertical line and point on the curve. The marginal cost to providing a declaration, η^t, is shown as a dashed red line. According to the model, areas with a vote margin at which the marginal return to a declaration exceeds the marginal cost will receive a declaration.

Figure A.2: The Marginal Return to Drought Declaration with Incumbency Effects



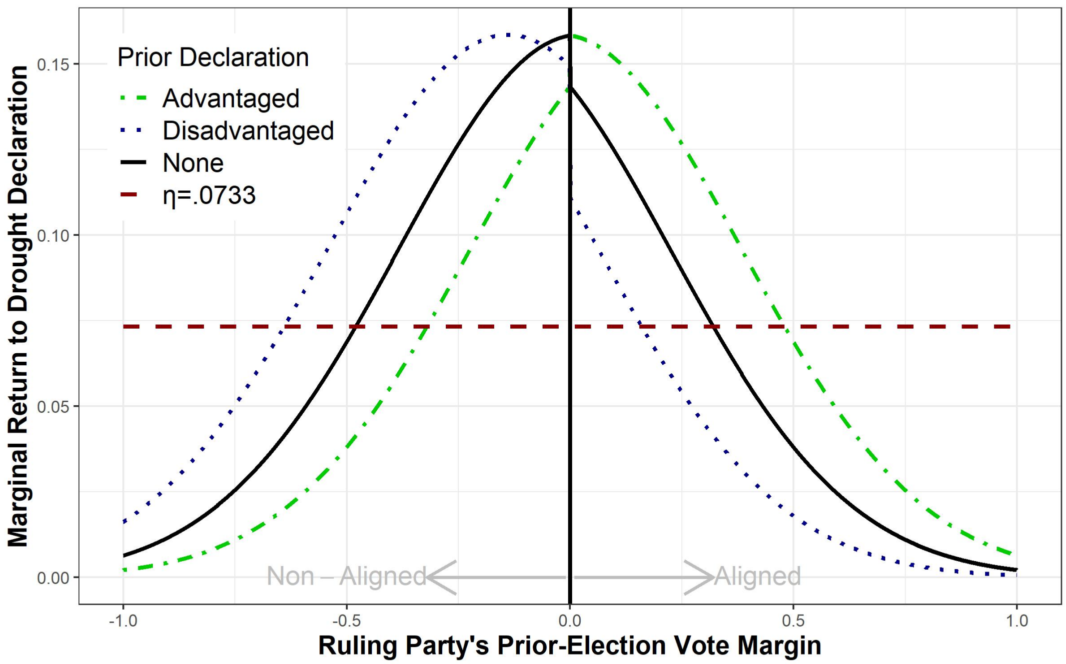
Note: This figure plots the marginal return to a drought declaration curve, as described by the left-hand side of Equation 2, for different possible values of the ruling party's (first election) vote margin; likewise, the figure includes the marginal cost of a declaration (left-hand side of Equation 2) represented by horizontal lines in the figure. This figure assumes $\theta_r(1) = \theta_r(0)$ and no shifts in support due to prior incumbency or prior declarations. For exposition, I consider 2,001 points along the ruling party's vote margin distribution and fix $\epsilon_{cr} \sim N(0, .04)$, and $\theta_r = .08$, and $N^t = 800$. The plot is split by a vertical line where the ruling party's vote margin is equal to zero: non-aligned constituencies fall to the left of the line while aligned constituencies fall to the right of the line. The figure plots the marginal return and associated marginal cost in the case with no incumbency advantage/disadvantage ($\zeta = 0$, solid black line), an incumbency advantage ($\zeta = .1$, dashed green line), and an incumbency disadvantage ($\zeta = -.05$, dotted blue line).

Figure A.3: The Marginal Return to Drought Declaration with Prior Incumbency Effects



Note: This figure plots the marginal return to a drought declaration, as described by the left-hand side of Equation 2, for different possible values of the ruling party's (first election) vote margin; likewise, the figure includes the marginal cost of a declaration (left-hand side of Equation 2) represented by a horizontal line in the figure. This figure assumes $\theta_r(1) = \theta_r(0)$ and no shifts in support due to prior declarations. For exposition, I consider 2,001 points along the ruling party's vote margin distribution and fix $\epsilon_{cr} \sim N(0, .04)$, $\theta = .08$, $\zeta = .05$ (incumbency advantage), and $N^t = 800$. The plot is split by a vertical line where the ruling party's vote margin is equal to zero: non-aligned constituencies fall to the left of the line while aligned constituencies fall to the right of the line. The figure plots the marginal return and associated marginal cost in the case with no prior (or lagged) incumbency effect (solid black line), an incumbency effect that benefited the current ruling party in the past election (dashed green line), and an incumbency effect that disadvantaged the current ruling party in the past election (dotted blue line). With the given parameters and assuming all constituencies fall into one of the three cases, the marginal cost happens to be the same in each case and is therefore only plotted once (dashed red line).

Figure A.4: The Marginal Return to Drought Declaration with Prior Declaration Effects



Note: This figure plots the marginal return to a drought declaration, as described by the left-hand side of Equation 2, for different possible values of the ruling party's (first election) vote margin; likewise, the figure includes the marginal cost of a declaration (left-hand side of Equation 2) represented by a horizontal line in the figure. This figure assumes $\theta_r(1) = \theta_r(0)$ and no shifts in support due to prior incumbency. For exposition, I consider 2,001 points along the ruling party's vote margin distribution and fix $\epsilon_{cr} \sim N(0, .04)$, $\theta = .08$, $\zeta = .05$ (incumbency advantage), and $N^t = 800$. The plot is split by a vertical line where the ruling party's vote margin is equal to zero: non-aligned constituencies fall to the left of the line while aligned constituencies fall to the right of the line. The figure plots the marginal return in the case with no prior (or lagged) incumbency effect (solid black line), a declaration that benefited the current ruling party in the past election (dashed green line), and a declaration that disadvantaged the current ruling party in the past election (dotted blue line). With the given parameters and assuming all constituencies fall into one of the three cases, the marginal cost happens to be the same in each case and is therefore only plotted once (dashed red line).

Appendix B Data

B.1 Block and District Names

The spelling of the names of Indian districts and blocks varies across the sources of data used in this paper. In order to match geographic units across data sources, I use exact name matches between any two data sources. For blocks, I use the state name, district name, and block name in the matching process as block names may be repeated across districts within a single state. Likewise, in the matching for district names I also use the state name. I then determine which blocks (or districts) in each data source are not paired and review each of the individual cases. In most cases, the lack of a match is due to a simple variation in spelling that can be adjusted by comparing the unmatched units. In a few cases, the name of a block's headquarters is listed instead of the name of the block itself and so I identify the correct match in these instances through web searches on the administrative units.

B.2 Official Drought Declarations Data

I construct a block-level panel dataset of official drought declarations for the period 2008 to 2019 for Karnataka and 2009 to 2019 for Andhra Pradesh and Telangana. The Karnataka State Natural Disaster Monitoring Centre (KSNDMC) provided a list of declarations for the full period except for the 2019 season, for which data comes from an official drought declaration publication. The Telangana State Development Planning Society (TSDPS) provided a list of official drought declarations for the full period at the block level as well. Annual lists of drought declarations for the blocks in Andhra Pradesh are collected from official drought declaration documents, except for the year 2013. Data for 2013 is based on a state report listing the number of blocks per district that received a declaration. For 7 districts no blocks received a declaration and in 1 district all blocks received a declaration; for these 8 districts, I am able to code the declaration indicator. However, for 5 districts a subset of blocks received declarations but I do not observe which blocks and so the declaration indicator is set to missing for 2013.

B.3 Political Data

The Election Commission of India (2019) and Bhavnani (2014) provide data on state Legislative Assembly elections in Andhra Pradesh/Telangana and Karnataka. From this data, I construct the two measures described in Section 2.2 as well as voter turnout and the Herfindahl-Hirschman Index (HHI) of vote shares. In order to connect this constituency-level political data to the block-level declaration and environmental data, block boundaries must be mapped to the political boundaries. I map blocks to 2008-boundary assembly constituencies using information provided in the delimitation documentation for each state (Election Commission of India, 2008).[55] In my sample of matched blocks-constituencies, about 92 percent of blocks map to a single constituency while the remaining blocks map to two or more constituencies. Therefore, to construct block-level political variables, for each block b in year t, I take the average of political variables over the n mapped constituencies $c(b)$ in the prior election $e(t)$, or

$$variable_{c(b)e(t)} = \frac{1}{n}\sum_{c(b)} variable_{ce(t)}.$$

Note, the *aligned* indicator at the block level is then an indicator that the average ruling party's vote margin was greater than 0.

Instrument Construction

In addition to the mapping described above, a second mapping is needed for instrument construction between 2008-boundary assembly constituencies and the 2004-boundary constituencies (the latter set of boundaries were actually designated in 1976). This constituency-to-constituency mapping is made using the delimitation documents Election Commission of India (1976) and Election Commission of India (2008) as well as a mapping provided by Iyer and Reddy (2013).[56]

Using this second mapping allows for the construction of an instrument based on information from the pre-delimitation, 2004 election. The goal of this instrument is to estimate the counterfactual vote margin, or what voters' support for each party would be if unaffected by local unobserved factors that also influence future declarations. However, an issue with using information from the 2004 election to estimate support for the ruling and opposition parties is that some of the parties from the 2008/9, 2013/14, and 2018/19 elections either did not exist in 2004 or did not run in all constituencies that they would later contest. Assigning a value of 0 for such a party-constituency observation would lead to a predicted vote share of 0 and so the vote margin would simply reflect the vote share of the remaining party, assuming that the party ran in 2004. Even in the case where a party did exist in 2004, it may have

[55] Based on available data, I was unable to match blocks in Hyderabad, Telangana to constituencies and so these blocks are excluded from the analysis; however, these are blocks that are not subject to drought declarations during the period of analysis.

[56] For a number of constituencies located in Bangalore, I am unable to construct a mapping between 2004-boundary and 2008-boundary constituencies so blocks that map to these constituencies are dropped from the sample.

had support in a given constituency but not contested the election because a coalition partner was running or the party did not anticipate sufficient support to win. Instead of assigning 0 baseline support, I assign the mean value of observed 2004 vote shares for ruling party and opposition party-constituency pairs; I chose the mean as it might be representative of how the party would have done had it run. For ruling and opposition party-constituency observations that can be matched to a 2004 vote share the mean vote share is .36 (.35 for opposition parties only and .38 for ruling parties only). As a robustness check, in Appendix Table C.8 I instead assign the first quartile value for the vote share of .28 (column 2) or the third quartile value of .46 (column 3). First, the result that declaration likelihood is decreasing in the absolute value of the vote margin is robust across these two alternative specifications. Second, the magnitude of the coefficient is larger than the OLS coefficient in all cases, though the magnitudes vary depending on which value is assigned for unobserved vote shares.

I also create there alternative instruments to study the robustness of the main findings. For the first, I increase the leave-out in the state-level shift in voters' support for a party to drop all constituencies located in the same district. Second, in order to construct an instrument in which all temporal change from *nearby* constituencies is removed from the shift factor, I utilize a publicly available map of modern constituencies. I find the centroid for each constituency polygon and identify all other centroids that lie within a 100 km radius (and the same state). Third, I reconstruct the instrument using data from the 1999 election, applying the same adjustment described above, for parties that did not run in a given constituency in 1999.

B.4 Environmental Data

I use the India Meteorological Department's .25x.25 gridded rainfall data from Pai et al. (2014) and the .5°-by-.5° gridded, model-calculated average monthly soil moisture for van den Dool et al. (2003).[57] In order to transition this gridded data to block-level variables, I use shapefiles for blocks in Karnataka and Andhra Pradesh/Telangana.[58] To get the block-level averages, I first reproject the gridded data to Cylindrical Equal Area, then convert the raster to a polygon and intersect it with the shapefiles (also re-projected to Cylindrical Equal Area). I use the area of each intersected polygon within a block to get the area-weighted average of rainfall or mean soil moisture. Due to the fact that the IMD rainfall is available for grid points that fall on land only, some blocks located on the coast are not completely covered by a rainfall grid polygon; for

[57]CPC Soil Moisture data is provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA.

[58]The shapefile used for Karnataka was provided by Professor Ashwini Chhatre while the shapefile for Andhra Pradesh/Telangana is from ML InfoMaps.

these blocks, I use the area-weighted average for the overlap. For four blocks for which there is no overlap, I use the average rainfall for a neighbouring block.

The normalized difference vegetation index (NDVI) data is provided on a per pixel basis, with a spatial resolution of 1 kilometer, for each of nine 16-day periods that overlap the primary (Kharif) growing season (Didan, 2015). To construct the NDVI for each block and 16-day period, I first convert the pixels to a gridded (raster) dataset and re-project the gridded data into Cylindrical Equal Area. I then overlap the block-level polygons with the NDVI gridded data and take the average of all points that fall within the block. The NDVI gridded data is very dense and so taking an area-weighted average of all points within a block (as is done for rainfall and soil moisture) for each 16-week period in the 12 years in this sample would be a very data-intensive process. The non-area-weighted average is instead used because it is calculable within a reasonable timeframe; however, because of the density of data points for NDVI, taking an area-weighted average might not be as important as for gridded datasets with more sparsely available data.

The guidelines offer specific variables and cutoffs that can be used for the soil moisture and NDVI data in order to generate indicators needed for meeting the sufficient condition for a declaration, particularly in the more recent drought manual. However, instead of generating indicator variables, I use the block-level average of NDVI for the nine 16-day periods and monthly mean soil moisture for the 4 months of the main agricultural season discussed above to flexibly control for soil moisture and vegetation. To account for variation in hydrological indices, I focus on groundwater levels and utilize monthly, district-level data (NWIC, 2020). The groundwater level data is not available at the block level or for all months, but is available for most districts in May and August. These months are also of particular relevance because they occur immediately before the growing season and at the end of the season, giving a sense of the variation in groundwater over the full season.

For crop area sown, the drought manual suggests that an indicator can be formed for area sown being less than 50 percent of total cultivable area (DAC, 2009). Again, data for crop area sown is only available at the district level and for the years 2008 to 2018 (DAC&FW, 2020). Because district boundaries in Karnataka and Telangana changed between 2008 and 2018, I combine districts that split post 2008 into the original 2008 district.[59] Instead of generating the measure suggested in the manual, which requires information on cultivable land, I generate the

[59]For three of Telangana's newly formed districts (Jangaon, Vikarabad, and Siddipet) the district was formed from two or three 2008-districts and so I assign the crop area statistics to the primary district from which it was separated.

ratio of the total area sown in the main agricultural season (the Kharif season) for a given year to the average total area sown during the season for the years 2008 through 2018; this measure is meant to capture how area sown in a given year varies from that of a *normal* year, measured as the average over the period.[60]

I also use this district-level data in the analysis of the impacts of drought and declarations on agricultural production. To do so, I also create measures of the share of cropped area sown that is devoted to each crop or crop group for each district-year.[61] One concern with utilizing the difference between early season NDVI and maximum NDVI as a proxy for agricultural production is that it does not take into account changes in cropping patterns. If drought or declarations impact the cropping decisions of households and this NDVI difference is crop specific, this would impact the interpretation of the results reported in Section 6. In order to ascertain whether this might be an issue, I re-estimate Equation 6 on the reduced sample in column 1 of Table C.5 and add the crop share controls in column 2. Importantly, the addition of controls for the crop shares does not impact the coefficients on prior-year drought or declarations.

Because rainfall indicators are the primary measure for determining declarations, I take the block-level area-weighted averages and construct indicators for drought-affected areas. According to the 2009 guidelines, the primary criteria for a drought declaration in the primary agricultural season is met if (1) the total rainfall for June and July is below 50 percent of normal (with or without a dry spell) or (2) the total Kharif-season rainfall (June to September) is below 75 percent of normal. To construct these indices, I start by constructing the ratio of current rainfall to the long-term-average rainfall, or

$$ratio^{period} = \frac{\text{current total rainfall in given period}}{\text{long-term-average rainfall for given period}}$$

for the relevant period of months or weeks.[62] Here a ratio of 1 indicates that the block received normal or average rainfall while a ratio less than (greater than) 1 indicates below-average

[60] For the six districts in Telangana from which Jangaon, Vikarabad, and Siddipet districts were separated, my measure of total crop area necessarily changes in 2016 because I only assign the newly-formed district to the primary 2008-district. However, when running the regression in column 7 of Table 5, where this crop area sown ratio is used as a control, I can also include an indicator for being in one of these six districts post 2016 and the interaction between the area ratio and the indicator and it does not significantly impact the results. The coefficient on the absolute value of the ruling party's vote margin becomes -.772 (s.e. .242) as opposed to -.766 (s.e. .244).

[61] I include shares for individual crops including cotton, dry chilies, black pepper, ginger, coriander, tumeric, arecanut, niger seed, tobacco, cashew nut, sugarcane, tapioca, and mesta. For the remaining crops, I include shares for crop groups: millets, grain, oilseeds, fruit, vegtables and tubers, or pulses and legumes.

[62] The long-term-average should consider 30 prior years, as a minimum. For a given year t, I take the average rainfall over the period 1998 to $t-1$.

(above-average) rainfall. I use these ratios themselves as continuous controls for rainfall in some specifications and also combine the ratios with cutoffs specified in the guidelines to create indicator variables. The baseline indicator for drought affected blocks (used throughout the paper) is then,

$$drought_{bt} = \mathbf{1}\{ratio_{bt}^{June/July} < .5 \vee ratio_{bt}^{June-Sept} < .75\}.$$

While this indicator is proscribed by the national guidelines for the majority of the sample period, there are other indicators of drought that might be used by state governments during the period. For example, during part of the sample period, official drought declarations in Andhra Pradesh/Telangana cite an alternative, state-specific cutoff for the June-September rainfall ratio: .75 for areas where normal rainfall is above 1000 millimeters; .80 where normal rainfall is 750-999.9 millimeters; and .85 where normal rainfall is below 750 millimeters (GoAP, 2013). I take the baseline drought indicator, described in the previous paragraph, and adjust the full-season criteria for Andhra Pradesh/Telanga to create an alternative indicator $drought_{bt}^{AP}$. Further, the 2016 national guidelines add an additional criteria, based on dry spells, to the two listed above to define the necessary condition for a drought declaration. According to the guidelines, dry spell is defined as 3-4 weeks of consecutive rainfall below 50% of normal following the onset of the monsoon. I do not attempt to estimate the beginning of the monsoon in each year, instead I create an indicator that takes a value of one if $ratio^{Week}$ is less than .5 for any consecutive 4 weeks during June to September.[63] Again, I construct an alternative indicator for drought-affected blocks that takes the baseline indicator and changes the value to one if the ratiois less than .5 for any consecutive 4-week period, $drought_{bt}^{DS}$. Appendix Table C.9 provides the results of estimating Equation 4 using each of the alternative drought indicators. While there are some small differences in the coefficient on the absolute value of the ruling party's vote margin, the results showing that declaration likelihood is higher in competitive areas is robust to these alternatives.

Finally, to identify blocks that might be considered urban, I use the harmonized nighttime lights dataset provided by Li et al. (2020) and overlay each image with block-level polygons. I then take an area-weighted average of data points as the block-level night lights value. I consider a block to be urban if its night lights in 2008 was above the 95^{th} percentile for all blocks in the sample.

[63] Also, prior to the change in guidelines, the Karnataka state government used rainfall deficiency, soil moisture, and more than 4 weeks of dry spell to determine drought declarations (GoK, 2016).

Appendix C Additional Tables and Figures

Table C.1: Instrument Construction for Vote Shares and Ruling Party Vote Margin

	Dependent variable:	
	$voteshare^{p}_{ce}$	$margin_{ce}$
	(1)	(2)
$\widetilde{voteshare}^{p}_{ce}$	0.290***	
	(0.038)	
$\widetilde{margin}_{ce}$		0.252***
		(0.044)
Observations	2,929	1,470
R^2	0.295	0.403
F-Statistic	58	33
Constituency FE	Yes	Yes
Election FE	Yes	Yes

Note: This table reports regressions of observed political variables on constructed political variables for each stage of instrument construction (see Section 4.1) at the constituency-election level. All specifications include constituency and election fixed effects. Column 1 reports results for a regression of observed vote shares on constructed vote shares for the ruling party and main opposition in each constituency. Columns 2 provides an estimation of the regression of the ruling party's vote margin on the constructed vote margin. The F-statistic for the constructed instrument is reported. Standard errors are clustered by constituency. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.2: Drought Declarations and Political Motivations, Alternative Functional Form

	$Declaration_{bt}$	
	(1)	(2)
$drought_{bt}$	0.192***	0.186***
	(0.007)	(0.007)
$margin_{c(b)e(t)}$	−0.013	−0.098
	(0.020)	(0.089)
$margin^2_{c(b)e(t)}$	−0.404***	−1.711***
	(0.079)	(0.563)
Observations	14,043	14,043
First Stage F-Stat (1^{st} Variable)		58
First Stage F-Stat (2^{nd} Variable)		22
KP First Stage F-Stat		10
Specification	OLS	IV
Block FE	Yes	Yes
State-Year FE	Yes	Yes

Note: This table reports an estimation similar to Equation 4 but the indicator for block b receiving a drought declaration in year t is regressed on the a quadratic in the ruling party's vote margin (instead of the absolute value) and an indicator for drought occurrence (OLS specification in column 1 and IV specification in column 2). All specifications include block and state-year fixed effects. The instrument construction for the ruling party's vote margin is explained in Section 4.1 and the results of the first-stage regressions are provided in Table C.3. The Sanderson-Windmeijer first stage F-statistics are reported for each of the endogenous variables followed by the Kleibergen-Paap Wald rk F statistic for the IV specification. The Anderson-Rubin Wald test has a p-value of 0.0002 for the IV specification. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.3: First Stage Regressions of Vote Margin and Squared Vote Margin on Instruments

	Column 2	
	$margin_{c(b)e(t)}$	$margin^2_{c(b)e(t)}$
	(1)	(2)
$\widehat{margin}_{c(b)e(t)}$	0.282***	−0.011*
	(0.026)	(0.007)
$\widehat{margin}^2_{c(b)e(t)}$	−0.769***	0.238***
	(0.132)	(0.054)
$drought_{bt}$	−0.0001	−0.004***
	(0.003)	(0.001)
Observations	14,043	14,043
R^2	0.436	0.603
Block FE	Yes	Yes
State-Year FE	Yes	Yes

Note: This table displays the results of the first stage regressions for the IV regression shown in column 2 of Table C.2. Column 1 of this table provides the first stage for the the ruling party's vote margin and column 2 shows the first stage for the square of the ruling party's vote margin. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.4: Robustness of Agricultural Production Results Instrumenting for Prior-Year Declaration with Prior-Year Drought

	$IHS(\Delta NDVI_{bt})$	$Declaration_{bt-1}$
	(1)	(2)
$Declaration_{bt-1}$	0.265***	
	(0.033)	
$drought_{bt-1}$		0.178***
		(0.007)
Observations	14,037	14,037
KP First Stage F-Stat		584
Specification	IV	First Stage
Block FE	Yes	Yes
State-Year FE	Yes	Yes
Env. Variables	Yes	Yes

Note: Column 1 of this table reports an IV estimation of Equation 6 where the dependent variable is the inverse-hyperbolic sine (IHS) of the NDVI difference, or the difference between maximum and early-season vegetation index, for block b in year t and prior-year drought becomes an excluded instrument for the independent variable of interest, the indicator for block b having received a declaration in the prior year, $t-1$. Column 2 reports the first stage regression of the declaration indicator for block b in $t-1$ on an indicator for drought occurrence in block b and year $t-1$. Both specifications include block and state-year fixed effects; the ratio of current June-September rainfall to its long-term average (and the squared ratio); the June/July rainfall to its long-term-average (and the squared ratio); and mean monthly soil moisture. The Kleibergen-Paap Wald rk F statistic is reported for the IV specification. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.5: Robustness of Agricultural Production Results Controlling for Cropping Patterns

	$IHS(\Delta NDVI_{bt})$	
	(1)	(2)
$Rain_{bt}$	0.263***	0.261***
	(0.046)	(0.045)
$Rain^2_{bt}$	−0.040**	−0.042***
	(0.017)	(0.016)
$drought_{bt-1}$	−0.008	−0.005
	(0.010)	(0.010)
$Declaration_{bt-1}$	0.032***	0.030***
	(0.009)	(0.009)
$drought_{bt-1} \times Declaration_{bt-1}$	0.035***	0.034***
	(0.012)	(0.012)
Observations	12,750	12,750
R^2	0.769	0.776
Block FE	Yes	Yes
State-Year FE	Yes	Yes
Env. Variables	Yes	Yes
Political Variables	Yes	Yes
Crop Shares	No	Yes

Note: This table reports estimations of Equation 6 where the dependent variable is the inverse-hyperbolic sine (IHS) of the NDVI difference, or the difference between maximum and early-season vegetation index, for block b in year t. The independent variables are the ratio of current June-September rainfall to its long-term average ($Rain$) in block b and year t, an indicator for drought occurrence in year $t-1$, and an indicator for receiving an official drought declaration in year $t-1$. Both specifications also include block and state-year fixed effects; mean monthly soil moisture; the June/July rainfall to its long-term-average (and the squared ratio); the absolute value of the ruling party's vote margin; the indicator for being aligned to the state ruling party; a comparable indicator for alignment to the federal ruling coalition; voter turnout; the HHI of vote shares; the number of candidates who ran; indicators for years since the last election; and indicators for the political party of the MLA(s). Additionally, column 2 also adds controls for the share of agricultural area sown devoted to each crop or crop group (for details, see Appendix B). Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.6: Planned Relief Expenditures Relative to Drought Occurrence/Severity

	Planned Relief Expenditures			
	(1)	(2)	(3)	(4)
$drought_{bt}$	-2.530		0.279	
	(2.800)		(2.896)	
$Rain_{bt}$		14.958		-18.151
		(23.387)		(27.575)
$Rain^2_{bt}$		-7.507		6.417
		(8.449)		(9.309)
$Area_{bt}$	0.016^{***}	0.016^{***}	0.016^{***}	0.015^{***}
	(0.004)	(0.004)	(0.005)	(0.005)
Observations	100	100	100	100
R^2	0.291	0.294	0.613	0.616
District FE	No	No	Yes	Yes

Note: This table uses data on planned relief expenditures for agricultural, horticultural, and animal husbandry subsidies in 2018 for blocks located in Karnataka (GoK, 2018). The table reports the results of specifications where the dependent variable is the amount of planned relief expenditure (in 100,000,000 rupees) and the independent variables are the geographic area of the block (in square meters) and an indicator for drought occurrence (column 1) or a quadratic in the ratio of June-September rainfall to is long-term average (column 2). Columns 3 and 4 repeat the specifications in columns 1 and 2, respectively, but adding district fixed effects. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.7: Impact of Drought and Declarations on Night Lights

	$IHS(NL_{bt})$		
	Average	50^{th} Percentile	5^{th} Percentile
	(1)	(2)	(3)
$drought_{bt-1}$	0.018	0.056**	−0.057*
	(0.012)	(0.024)	(0.030)
$Declaration_{bt-1}$	−0.006	−0.012	0.065***
	(0.007)	(0.013)	(0.022)
$drought_{bt-1} \times Dec_{bt-1}$	−0.024*	−0.049*	−0.005
	(0.014)	(0.027)	(0.038)
Observations	12,268	12,268	12,268
R^2	0.859	0.729	0.746
Block FE	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
Env. Variables	Yes	Yes	Yes
Political Variables	Yes	Yes	Yes

Note: This table reports estimations of Equation 6 where the dependent variable is the inverse-hyperbolic sine (IHS) of night lights for block b in year t (sample is limited to blocks with 2008 nigh lights below the 95^{th} percentile). Column 1 considers the area-weighted average light and columns 2 and 4 consider the median and $5th$ percentile of night lights within a block, respectively. The independent variables are an indicator for drought occurrence in year $t-1$, and an indicator for receiving an official drought declaration in year $t-1$. Controls include block and state-year fixed effects: the ratio of current June-September rainfall to its long-term average (and squared ratio); mean monthly soil moisture; the June/July rainfall to its long-term-average (and the squared ratio); the absolute value of the ruling party's vote margin; the indicator for being aligned to the state ruling party; a comparable indicator for alignment to the federal ruling coalition; voter turnout; the HHI of vote shares; the number of candidates who ran; and indicators for the political party of the MLA(s). Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.8: Robustness to Alternative Baseline Vote Share Assumptions

	Parties Missing a 2004 Vote Share Assigned:		
	Mean	1^{st} Quartile	3^{rd} Quartile
	(1)	(2)	(3)
Panel A:		$Declaration_{bt}$	
$drought_{bt}$	0.184***	0.188***	0.183***
	(0.008)	(0.008)	(0.008)
$\lvert margin_{c(b)e(t)}\rvert$	−0.909***	−0.550**	−1.079***
	(0.302)	(0.257)	(0.336)
Observations	14,043	14,043	14,043
Panel B:		$\lvert margin_{c(b)e(t)}\rvert$	
$\lvert \widehat{margin}_{c(b)e(t)}\rvert$	0.148***	0.156***	0.132***
	(0.038)	(0.040)	(0.035)
$drought_{bt}$	−0.009***	−0.009***	−0.009***
	(0.002)	(0.002)	(0.002)
Observations	14,043	14,043	14,043
R^2	0.582	0.582	0.582
KP First Stage F-Stat	15	15	14
Block	Yes	Yes	Yes
State-Year	Yes	Yes	Yes

Note: Panel A of this table reports IV estimations of Equation 4, where the indicator for block b receiving a drought declaration in year t is regressed on the absolute value of the ruling party's vote margin and an indicator for drought occurrence. Panel B reports the first stage regression for each IV specification. Column 1 reports the specification with the baseline instrument, where parties that did not run in a constituency in 2004 are assigned the mean observed vote share. Columns 2 and 3 instead use an instrument where the first quartile and third quartile, respectively, of the observed vote shares is assigned to those parties. The Kleibergen-Paap Wald rk F statistic for the endogenous variable is reported. The Anderson-Rubin Wald test has a p-value of 0.0000 in columns 1 and 3 and 0.0136 in column 2. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

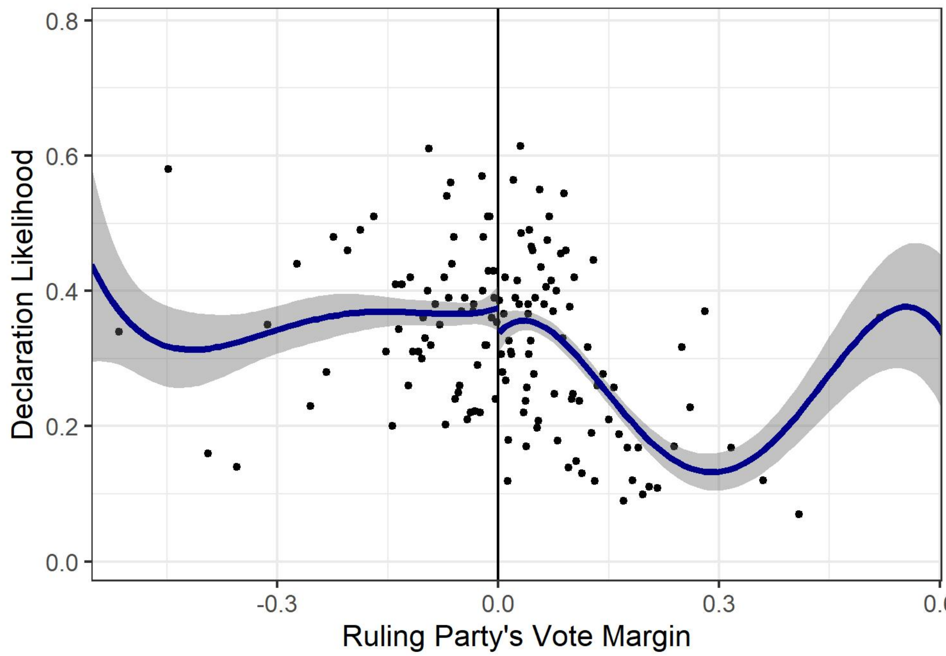
Table C.9: Robustness to Alternative Definitions for Drought-Affected Blocks

	$Declaration_{bt}$		
	(1)	(2)	(3)
$drought_{bt}$	0.184***		
	(0.008)		
$drought_{bt}^{AP}$		0.201***	
		(0.008)	
$drought_{bt}^{DS}$			0.119***
			(0.007)
$\lvert margin_{c(b)e(t)} \rvert$	−0.909***	−0.882***	−0.997***
	(0.302)	(0.306)	(0.317)
Observations	14,043	14,043	14,043
KP First Stage F-Stat	15	15	15
Block	Yes	Yes	Yes
Year	Yes	Yes	Yes
Election Cycle	Yes	Yes	Yes

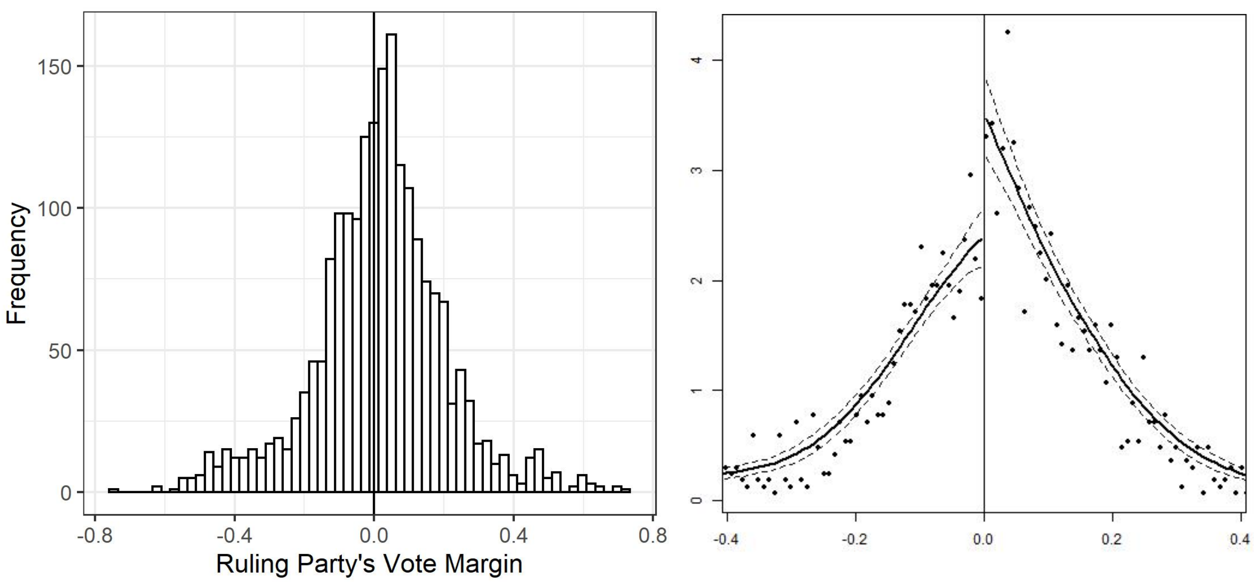
Note: This table reports IV estimations of Equation 4, where the indicator for block b receiving a drought declaration in year t is regressed on the absolute value of the ruling party's vote margin and an indicator for drought occurrence. Column 1 utilizes the baseline indicator for drought while columns 2 and 3 use alternative indicators for drought-affected blocks described in Appendix B. The Kleibergen-Paap Wald rk F statistic for the endogenous variable is reported. The Anderson-Rubin Wald test has a p-value of 0.0000 in columns 1 and 2 and .0001 in column 3. Standard errors are clustered by block. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure C.1: Official Drought Declaration Likelihood for Aligned and Non-Aligned Blocks

(a) Likelihood of Official Drought Declaration versus Ruling Party's Vote Margin

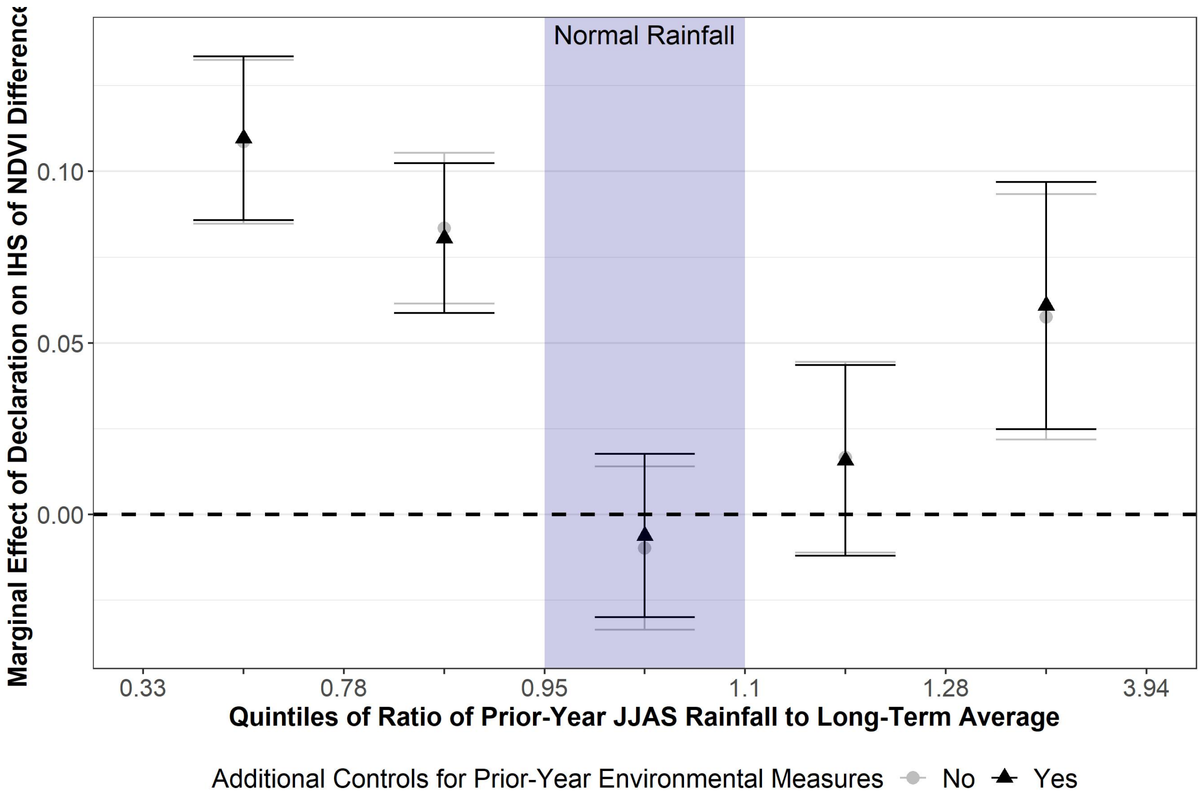


(b) Distribution of Running Variable



Note: This figure provides information relevant to a regression discontinuity design testing for the affect of being aligned to the ruling party (having a positive vote margin) on the likelihood a block receives an official drought declaration. Panel A plots a regression of the indicator for a block receiving a declaration on a fourth order polynomial in the running variable, the ruling party's vote margin, allowing for a discontinuity at a vote margin of 0; in addition, the figure includes a binscatter of the mean declaration likelihood against the mean vote margin where each point represents about 100 block-year observations. Panel B considers constituency-election observations, showing the distribution of the running variable in a histogram (left) and a non-parametric regression of the distribution allowing for a discontinuity at a vote margin of 0 (right) as in McCrary (2008). The coefficient estimate for the discontinuity in the density is .389 (s.e. .093) suggesting that, at least in some elections in the sample, the ruling party is more likely to win a close election than an opposition party.

Figure C.2: Impact of Declarations on Agricultural Production Controlling for Additional Prior-Year Environmental Measures



Note: This figure plots coefficient estimates and confidence intervals for an estimation of Equation 6 where the dependent variable is the inverse-hyperbolic sine (IHS) of the NDVI difference, or the difference between maximum and early-season vegetation index, for block b in year t and the indicator for drought has been replaced by indicators for the quintile of the prior-year rainfall shock distribution. The rainfall shock is measured as the ratio of June-September rainfall in the prior-year to its long-term-average. The figure displays the coefficient estimates for the declaration indicator interacted with quintile of the prior-year rainfall distribution and the x-axis provides the range of prior-year rainfall shock values for each quintile. The lowest quintile then displays the impact of declarations in areas affected by a negative rainfall shock (less than 78% of normal rainfall) while the highest quintile contains areas with excessive rainfall (more than 28% above normal). The third quintile represents areas with rainfall around the average (about a ratio of 1). Repeating the results shown in Figure 4, the first set of coefficients (grey) are from a regression that controls for block and state-year interacted fixed effects; mean monthly soil moisture; the June-September rainfall to its long-term-average (and the squared ratio); the June/July rainfall to its long-term-average (and the squared ratio); the absolute value of the ruling party's vote margin; the indicator for being aligned to the state ruling party; a comparable indicator for alignment to the federal ruling coalition; voter turnout; the HHI of vote shares; the number of candidates who ran; indicators for years since the last election; and indicators for the political party of the MLA(s). The second set of coefficients (black) are for a regression that additionally controls for the prior-year NDVI difference; prior-year monthly soil moisture; and the prior-year June/July rainfall to its long-term-average (and the squared ratio). Standard errors are clustered at the block level.