The Political Consequences of Resource Scarcity: Targeted Spending in a Water-Stressed Democracy*

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Abstract

We study whether resource scarcity enhances the scope for targeted spending in India. Farmers without access to groundwater during dry seasons cope using a large public-aid program controlled by local politicians. We leverage a multidimensional regression discontinuity for exogenous variation in whether local politicians are aligned with the state's ruling party. We find that the state government channels disproportionate funds to politically-aligned jurisdictions in water-stressed areas and gains votes in subsequent elections. However, we find no partisan differences in aid allocation for non-water-stressed areas, suggesting a selective targeting of public funds to garner votes in the highest-return regions.

JEL Codes: D72, H53, I38, O13, Q25

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1 Introduction

Government accountability is a cornerstone of democracy. An active electorate should reward politicians who provide aid during a crisis (Besley and Burgess, 2002). But the aid disbursed to alleviate a crisis can also be a means to manufacture popularity. It is well-documented that politicians in India, for instance, provide selective access of services to prospective voters (Cole, 2009; Mahadevan, 2021; Asher and Novosad, 2017), misdirect aid to regions based on the highest political returns (Tarquinio, 2021), and disburse aid right before an election (Cole et al., 2012). But there is a deeper risk that the crisis itself engenders hardship that political machines may exploit to entrench their power. Wade (1982), for instance, details how unkempt and dysfunctional canals enabled a clientelistic bureaucracy in South India to extract rents from the populace. The system benefited both the bureaucrats and the politicians who nominally oversee them, leaving little reason to fix the canals. But do these old anecdotes necessarily represent a systemic tendency for politicians to exploit a sustained crisis to further their interests?

The old question has new stakes during the global climate crisis. Recent research has shown that climate change, over-exploitation, and access to cheap electricity for irrigation have contributed to a rapid decline in water levels around the world (Asoka et al., 2017; Wu et al., 2020; van der Gun, 2012).[1] Drier conditions can create poverty and inequality in rural societies (Sekhri, 2014), leaving rural households more reliant on government-controlled programs. Their need may be exploited by a ruling party to target aid that they control in order to buy or retain votes. The risk is higher in developing countries, which may lack institutional checks to resist such actions even as they bear the greatest burden from climate change and resource shortages (Burgess et al., 2017, 2014; Carleton et al., 2020). This paper presents direct evidence showing that an exogenous shortage of resources causes strategic changes in targeting that may yield political returns.

We test whether the ruling party of the Indian state of West Bengal exploited groundwater depletion to win votes through its control over a major antipoverty program. West Bengal's water table has been in decline for decades (Figure 1). Groundwater in many areas is too deep to

[1] One of the major channels through which climate change can affect groundwater is due to its effect on increasing temperatures precipitating the higher frequency of droughts. This puts great pressure on groundwater use to meet basic needs, an effect that may intensify as climate change worsens (van der Gun, 2012)

access without unaffordable drilling technology. During the dry months after the monsoon harvest, many farmers rely on jobs provided through a public works program created through the National Rural Employment Guarantee Act (henceforth referred to as NREGA). Though funded by the central government, state governments exert great discretion over which village governments (gram panchayats) receive funds, and these panchayats further control which households receive jobs (Government of India, 2013). Although NREGA is not the only antipoverty program managed by local officials, it accounts for over 80 percent of the funds they control (Dey and Sen, 2016).

A naive analysis might suggest these funds are allocated based purely on need. Figure 1 shows no ex-ante correlations between whether an area is dry and its support for the ruling party (Panel B, right). Nevertheless, these drier areas receive a higher per-household allocation of NREGA labor (Panel B, left). But local officials often serve as the frontline workers of the political machine (Shenoy and Zimmermann, 2022; Bussell, 2019). The state government may have an incentive to channel funds through its co-partisans, who can target the funds to maximize the ruling party's election returns. Do the seemingly apolitical patterns in Figure 1 mask favoritism based on the allegiance of the local officials who ultimately control the funds?

We test whether the state ruling party allocates disproportionate funds, and wins disproportionate votes, in water-stressed areas controlled by its co-partisans. We derive variation in whether the ruling party controls the local government from the 2013 local council election. Different combinations of local victories affect the composition of the council and ultimately the party holding the majority. We use the seat-level vote shares of these individual races to construct a multidimensional running variable that summarizes, in a single real number, the distance from the actual outcome to an outcome where the ruling party won an absolute majority. In the neighborhood of this cutoff, all unobservable confounders should be continuous in the running variable. Only control of the council changes discontinuously at the cutoff. We test whether ruling party councils received larger aggregate labor allocations, and whether their jurisdictions returned a larger share of votes for the ruling party in the subsequent 2014 national election.

First, we find that, as predicted, panchayats controlled by the ruling party receive disproportionately large allocations through the make-work antipoverty scheme. These allocations are directed specifically at ruling party panchayats that are water-stressed. In effect, water-stressed areas narrowly controlled by the ruling party's local officials receive discontinuously more aid than equally water-stressed areas controlled by the opposition.

Second, in response to this selective aid, we find that the ruling party's national vote share is discontinuously higher in co-partisan areas, and specifically, the impact is concentrated in areas facing water stress. Meanwhile, there is no difference in vote returns or program allocations between ruling party and opposition areas that face no water stress. Together, these results are consistent with the hypothesis that in areas where climate stress reduces opportunities for private employment, the ruling party selectively misallocates NREGA jobs to tilt elections in its favor. These results suggest aggregate patterns like those shown in Figure 1 can make a government appear altruistic while obscuring political targeting.

Although we identify water stress in our main results by separating areas into those with above and below median levels of groundwater, we also verify that our results are not driven by a spurious regressor merely correlated with the level of groundwater. We follow Sekhri (2014) by leveraging variation in access to water generated from an exogenous technical constraint that makes drilling wells deeper than 8 meters discontinuously more expensive.[2] We show that our results hold (and in many cases become stronger) when we estimate our regression discontinuity results across an additional discontinuity: comparing areas just above versus below the 8 meter cutoff.

These results are unlikely to have a benign explanation. If the ruling party were merely focusing its aid on more desperate regions, we would not expect to find favoritism towards areas controlled by co-partisans. This favoritism is all the more salient, considering we find no evidence of differences in program allocation across partisan lines in areas that do not face water shortages. It is also implausible that the discontinuity in water-stressed areas arises from simple administrative frictions between state and local officials of different parties. We show in the appendix that *even within a panchayat*, areas that have historically supported the AITC get more jobs when the AITC gains an absolute majority (consistent with the findings in Shenoy and Zimmermann, 2022). And as we describe in Section 2, there is ample anecdotal and survey evidence

[2]This cutoff is based on the findings in Gibson and Singer (1969), where a depth of 8 meters is the largest effective depth that a centrifugal pump can function at.

that local politicians reward villagers for their votes on behalf of national political parties.

The mechanism behind our hypothesis does not rest on water scarcity per se. Any economic disaster, including the persistent disaster of poverty, may create similar incentives for political targeting. We focus on water scarcity because unlike other drivers of poverty and food insecurity, it is likely to worsen without major intervention. Thus even as poverty overall has been falling over time (Ravallion, 2020), declining water levels pose a countervailing force that may abruptly create severe regional hardship when groundwater becomes inaccessible. All things equal, water scarcity can exacerbate inequalities in access to aid along political lines.

Our main contribution is to the literature on resource shortages and political control. The most related paper (Bobonis et al., 2022) shows complementary evidence that the demand for clientelism falls in response to a drop in the vulnerability of drought-affected households who are provided water cisterns as a part of an experiment. Conversely, there is a rich literature showing that resource shortages can cause instability by reducing the opportunity cost of insurgency (Blattman and Miguel, 2010; Carreri and Dube, 2017; Oeindrila and Vargas, 2013; Caselli et al., 2015). Standard models of vote-buying suggest each marginal dollar of targeted funds will buy more votes (Stokes et al., 2013), thereby also reducing the opportunity cost of targeted spending. Our findings suggest that ruling parties respond to this new incentive by engaging in more targeted spending, and the areas they target do return more votes. The tools used by governments to provide selective access to prospective voters have been studied before in other contexts (Cole, 2009; Mahadevan, 2021; Asher and Novosad, 2017), as have studies looking at selective government response to disaster relief (Cole et al., 2012; Tarquinio, 2021). Our paper provides new empirical evidence highlighting their relevance to resource stress.

Our work also has implications for the literature on the effects of climate change. Previous studies on climate change have largely focused on its impact on health outcomes and morbidity (Deschênes and Greenstone, 2011), productivity and economic growth (Graff Zivin and Neidell, 2012), and conflict (Miguel et al., 2004). But in the absence of proper management, climate change may also steadily deplete water levels (Green, 2016). Given that climate change may also bring drier conditions and more frequent droughts, the dependence on groundwater is set to increase steadily over time (van der Gun, 2012). A decline in water tables specifically has been shown to reduce agricultural productivity, firm performance (Liu and Sekhri, 2021), and the availability of drinking water, while also triggering violence (Sekhri, 2014). Our study now reveals a new danger: water shortages can perpetuate and magnify the incentive to tilt elections by misallocating government aid.

We also contribute more broadly to the literature on clientelism and the targeting of public funds for political gain (for a review, see Healy and Malhotra, 2013; Bardhan and Mookherjee, 2020). Much of this literature studies how funds are targeted to important constituencies or during salient points in the political cycle (Brender and Drazen, 2008; De la O, 2013; Healy and Lenz, 2014; Labonne, 2013; Manacorda et al., 2011; Baskaran et al., 2015; Khanna and Mukherjee, 2020) or specifically examines the inherent quid pro quo of clientalism (Sukhtankar, 2012). Our work is perhaps unique in highlighting resource shortages as a catalyst that strengthens the power of politicians over their voter bases. We show evidence of targeting based on water stress, but specifically in regions that are politically aligned with the ruling party. In doing so, this paper is also relatively rare in having plausibly exogenous variation in two distinct features being targeted: partisan alignment and the level of water stress.

We identify a potential new threat in the already troubling shortages of water around the world. If the gradual decline in water levels visible in Figure 1 continues and is mirrored in other developing countries, the number of people left desperate for aid will increase—and with it, the potential for targeted spending. The misallocation of aid in West Bengal has real economic consequences. A back-of-the-envelope calculation suggests households in water-stressed areas controlled by the opposition may have to cut their already meager consumption by as much as 20 percent at some point during the dry season. Households in equally stressed areas controlled by the ruling party, however, receive enough aid to almost fully compensate their lost income.[3] In times of scarcity, the power to allocate aid could, conversely, be the power to allocate hardship. Politicians who abuse this power may prove difficult to unseat.

2 Background and Natural Experiment

[3] Our calculation combines our estimates with those of Sekhri (2014) and summary statistics from the Indian Human Development Survey (Desai and Vanneman, 2018). We assume that Sekhri's estimates of the impact of water stress on monthly income are a uniform reduction in all months, and that our estimates of the average dry season impact are concentrated in the driest month.

2.1 Elections in India

India's political system is federal, with the central government being governed by a national parliament elected in a Westminster system contested by many political parties.[4] Each of India's states also has a legislative assembly that is elected and governs under a similar system, resulting in a ruling party that controls the majority in the legislative assembly, and whose leader is the chief minister. Each state also has its own system of local government. In rural West Bengal, each cluster of 5 to 15 villages is governed by a village council, the gram panchayat (the term "panchayat" also refers to the area governed by the council). West Bengal is atypical in also using a Westminster model for its local elections. Voters are divided into local constituencies that each elects a member to the gram panchayat, and these members elect a council president.

Unlike most other states, local elections in West Bengal are explicitly partisan. The 2013 local election was largely a contest between the state's incumbent ruling party, the All-India Trinamool Congress (AITC), and several weaker opposition parties.[5] As we describe in the next section, the results of this local election created quasi-random variation in whether a panchayat was governed by the ruling party versus being governed by the opposition or a coalition.

The ruling and opposition parties aim to grow their national profile and increase their influence on policy. Just one year after the local election, India held its 2014 national election. The ruling party and the major opposition parties fielded candidates for national parliament, and the performance of the ruling party is one of the two key outcomes we study.

2.2 NREGA Allocation

The connection between the national election and the local election that preceded it lies in India's federal structure. The biggest antipoverty programs are financed by the national government but administered by the state and local governments. The National Rural Employment Guarantee Act (NREGA), a massive make-work scheme designed to support farmers during the dry season, is the most prominent example. Though the money comes from the center, the state government holds enormous power over how many NREGA public works projects, and

[4]Following the British system, India also has two houses, one with democratically elected members (Lok Sabha), and the other made of nominated leaders (Rajya Sabha). The government is run by an executive consisting of the majority party in the Lok Sabha. The executive elects the prime minister, the head of government.

[5]Most prominently, the Communist Party (Marxist), the Indian National Congress, and the Bharatiya Janata Party.

thus how many days of NREGA labor, are allocated to each gram panchayat.[6] At this stage, there is potential for the state government to make unequal allocations across panchayats, particularly towards their co-partisan panchayats.

Given these projects, the local council compiles a list of households requesting labor (Government of India, 2013). Though in principle every household that wants labor is entitled to 100 days, in practice there are far fewer jobs than job-seekers. This shortfall gives the local council effective control over which individuals will be employed on each of these projects. This subsequent stage of targeting jobs is potentially a large part of the incentive of the state ruling party to allocate more jobs to their co-partisans (Shenoy and Zimmermann, 2022).

2.3 Partisan Targeting and Antipoverty Programs

The federal structure of India's system increases the potential for politically targeted spending. Local politicians are in a position to use their control over antipoverty programs to selectively target recipients, which they can potentially turn to the service of their party. National candidates openly acknowledge relying on local politicians for their campaigns. One member of parliament noted in an interview that "When campaigning, I rely extensively on the help of panchas and sarpanchas," or councilors and council presidents (Thomas Bohlken, 2016, p. 62). Dunning and Nilekani (2013) find in a survey of local politicians across three Indian states that the average councilor is expected to spend 3.4 hours per week doing work for their political party, and some 30 percent of council presidents acknowledged providing support to co-partisans during elections.

The support of these politicians matters because they often command the loyalty of voters through their control over government resources. Dunning and Nilekani (2013) also find in a separate survey of voters that nearly three-quarters asked the council president for access to government welfare schemes, and their chances of receiving such benefits were roughly 30 percent higher if they shared the party affiliation of the president. Tellingly, the effect is especially large for jobs received through NREGA.

The existence of this patron-client relationship is no secret. One local official quoted in

[6] To be precise, the council proposes public projects that must be approved by block program officers and engineers, who are employees of the state (Government of India, 2013). The state can influence the allocation of projects by prioritizing the approval of some projects over others.

Ziegfeld (2017) explicitly stated that

> This village and the surrounding villages are my family's jagir [feudal estate]. It is in my blood to do something for others. After my graduation [from college], people came to me with their problems. I became sarpanch [equivalent of a rural mayor], running unopposed. Villagers came by the thousands to vote for me. (Ziegfeld, 2017, p. 105)

Since antipoverty funds may potentially be mis-targeted for political ends, it is rational for the ruling party to channel disproportionate funds to panchayats controlled by their co-partisans while cutting off the opposition.

The key question we answer is whether the ruling party has greater scope to raise votes in areas that lack access to water. In areas where groundwater is buried too deeply to access, farming is difficult or impossible during the dry season, reducing the demand for hired labor in turn. Farmers and laborers in these areas may be especially desperate for income during the dry season. Our hypothesis is that (1) the ruling party can only trade NREGA jobs for votes when it controls the local council, and (2) the ruling party's vote trading is especially effective in these drier areas. The ruling party may therefore target disproportionate resources and reap disproportionate votes in co-partisan panchayats in water-stressed areas.

3 Data

3.1 Election and NREGA data

We obtain the universe of election outcomes for the 2013 Gram Panchayat Elections in West Bengal from the State Election Commission website. We combine data for over 100,000 candidates with digitized records of polling station-level election results from the 2014 national election (certified by the Chief Election officer). We then geo-locate these polling locations using data from Susewind (2016).[7]

We link these election outcomes with data constructed from administrative records on 11 million NREGA 'job cards.' Each of these records includes the name of the recipient, their panchayat of residence, and how many days they received (if any). In total, the 11 million records

[7] Our unit of observation is actually the polling building because we cannot distinguish between distinct polling booths if located on the same site.

catalog 300 million distinct job spells. These were obtained from the publicly available monitoring and reporting website for the NREGA. Using the election and NREGA data, we then construct a running variable for the multi-dimensional regression discontinuity design outlined in Section 4.1.

3.2 Groundwater data

We measure groundwater levels using readings from monitoring wells maintained by the Central Ground Water Board, which monitors 1,048 unique wells in the state of West Bengal. This data is collected annually, and provides four measures of depth to water for each monitoring well: pre-monsoon (April to June), monsoon (July to September), post-monsoon wet season (October to December) and post-monsoon dry season (January to March).

We use GIS interpolation (inverse-distance weighting) to construct well depths for every polling location during the 2014 post-monsoon dry season, which just preceded the 2014 election. The "depth" refers to how far one must drill to access the water. A higher depth implies less accessible water. Our main results classify a polling location as "water-stressed" if the well depth is above the median. Figure 2 shows the variation in groundwater depth across the state of West Bengal. Pockets with low groundwater depth are located in several parts across the state. They do not seem to be concentrated in areas with specific topography or socio-economic features.

To verify that our main results reflect differences in access to groundwater rather than selection bias, we also define an alternative measure of water-stress that exploits a natural experiment created by the mechanics of water extraction. Specifically, we consider 8 meters below ground level to be a major threshold, above which the costs of drilling to extract water rise exponentially. This phenomenon arises from exogenous physical challenges related to using a centrifugal pump to draw water. These pumps function by exploiting the difference in atmospheric pressure within the well. The atmospheric pressure outside the well exceeds that within, exerting an upward push on the water that raises it to the surface.

But beyond a depth of 8 meters, atmospheric pressure alone cannot create enough suction. The technology required to draw water from deeper levels is significantly more costly (Gibson and Singer, 1969; Spellman, 2004). We use this threshold as exogenous variation following Sekhri

(2014). Applying this method requires more precise measures of water depth. All analysis using the 8 meter cutoff measures water depth at each polling location using only the nearest monitoring well and keeping only stations within 5 kilometers of a monitoring well.

4 Design

4.1 Defining the Running Variable

The standard natural experiment for whether a party controls an elected office is the close-election regression discontinuity design (George and Ponattu, 2020; Nellis et al., 2016; Prakash et al., 2019). If the village council president were directly elected—as they are in most Indian states—we could compare outcomes in a panchayat where the candidate of the ruling party wins a close election with one where it loses. That is, we would estimate a simple regression discontinuity using the vote share of the ruling party candidate as the running variable. But West Bengal's panchayats follow the Westminster system. Each panchayat is divided into wards that elect a representative, and the representatives collectively appoint a council president. The election of an entire council makes the problem of defining a running variable more complex, as no single vote share determines the presidency.

We follow the approach of Shenoy and Zimmermann (2022), which constructs a multidimensional running variable from the vote share of the ruling party across all wards in the panchayat (see, for example Feigenbaum et al., 2017; Folke, 2014; Katakorpi et al., 2013; Zajonc, 2012). Suppose a village council has five seats, and the ruling party wins just one while losing the others by margins of 10, 20, 30, and 40 percent. Since it would have had to have won two more seats to hold an absolute majority, the shortest "distance" to the majority would be to flip the outcomes of the seats it lost by 10 and 20 percentage points.

These margins can be aggregated to a single metric using any of several distance metrics. In our main specifications we simply add up the loss margins of the seats needed to barely hold a majority. In this example, the distance would be $10 + 20 = 30$ percentage points, or 0.3. This is simply the one-norm in five-dimensional space (see Appendix A.3 for details), and the principle can be applied to a council of any size.[8] Given this definition, a panchayat will be just over

[8]If a council has an even number of seats, we assume an absolute majority requires $N/2 + 1$ seats.

the cutoff either because the ruling party won a single ward by a narrow margin, or because it won several wards by even narrower margins. The approach generalizes to any p-norm in N dimensional space (Reardon and Robinson, 2012; Wong et al., 2013; Cattaneo et al., 2016; Feigenbaum et al., 2017). We show in Appendix A.5 that the main results hold for two other choices of p.

4.2 Specifications

We estimate impacts on NREGA allocations at the panchayat level because only a small number of job cards can definitively be linked to a particular polling station. Let L_{it} be the average per-household NREGA allocation during the dry season (rabi) to panchayat i in year $t = 2014, 2015, 2016$. Let M_i be an indicator for whether the ruling party holds an absolute majority in the panchayat, and d_i be the distance to that outcome under some distance metric. Our preferred metric is the 1-Norm, but we show in Appendix A.5 that the results hold with the 2-Norm and Infinity-Norm. Let X_i be a vector of control variables (usually parliamentary and constituency fixed-effects). We estimate

$$L_{it} = \alpha_0 + \alpha_1 d_i + \alpha_2 d_i M_i + \beta M_i + X_i \boldsymbol{\psi} + \varepsilon_{it} \qquad \text{for } i \text{ such that } |d_i| < h \tag{1}$$

where h is the optimal bandwidth calculated using the method of Calonico et al. (2014), though in Appendix A.4 we show robustness to the precise choice of bandwidth. Observations are weighted by their distance to the cutoff using a triangular kernel, and standard errors are clustered by panchayat. As the Calonico et al. (2014) estimator has trouble calculating an optimal bandwidth in specifications that control for fixed effects, we simply use the optimal bandwidth for the analogous regression without fixed-effects. The coefficient β estimates the size of the discontinuity—that is, the impact on the panchayat's per-household NREGA allocations when the ruling party just barely takes an absolute majority on the local council.

We estimate a similar specification for the political impacts. Since we measure both vote shares and geocoordinates for individual polling locations, we make the polling location the the unit of observation in this specification. Let V_{is} be the fraction of votes cast for the ruling party's parliamentary candidate in panchayat i and polling location s relative to candidate's vote share in the entire parliamentary constituency. This variable, which we sometimes refer to as the "vote lean," measures how much more supportive the location is than the constituency as a whole. Note that there are no time subscripts because we only observe vote shares for one election, the 2014 national election. We estimate

$$V_{is} = \alpha_0 + \alpha_1 d_i + \alpha_2 d_i M_i + \beta M_i + X_i \boldsymbol{\psi} + \varepsilon_{is} \qquad \text{for } i \text{ such that } |d_i| < h, \tag{2}$$

The coefficient β estimates the impact on the ruling party's vote share when it barely takes an absolute majority council.

Our identification assumption is "continuity" as defined by Skovron and Titiunik (2015). We assume that all unobservable confounders that covary with both AITC control and the outcome are continuous in the running variable. Then observations away from the cutoff are used to estimate the local linear "control functions." As a consequence, the optimal bandwidth selector may choose a wider bandwidth than is standard in univariate "close election" designs to minimize the mean-squared error of the control functions. But we show in Appendix A.4 that the main results hold at even very narrow bandwidths.

5 Results

First, we find that the ruling party of the state government is directing additional support to local councils controlled by its co-partisans, but only in areas that are water-stressed. Table 1A tests for differences in the average per-household NREGA allocation to a panchayat when the ruling party wins a bare majority on the council. Columns 1 and 2 show estimates of Equation 1 on the overall sample, first without, and then with district and constituency fixed-effects. The average household in a panchayat controlled by the ruling party gets 1 extra day of labor during the dry seasons of 2014 through 2016, a roughly 13 percent increase over households in panchayats outside its control. The next two columns show that this increase is largely driven by the sub-sample of panchayats that are "water-stressed" (where the depth one must drill to find water exceeds the median). Water-stressed panchayats receive an extra 1.5 to 1.7 days of labor per household. Areas that are not water-stressed (Columns 5—6) receive a statistically insignificant

0.6 days of labor. This contrast is visualized in Figure 3, which plots binned means of the outcome against the running variable. The top panel of the figure confirms the estimates of Table 1A.

Second, our estimates show the same pattern in the ruling party's national vote share relative to the overall share in the constituency. Controlling the local council only benefits the ruling party's national candidate in areas that are water-stressed. Columns 1 and 2 of Table 1B show estimates of the effect of controlling the local council on national election outcomes (Equation 2) in the overall sample, first without, and then with district and constituency fixed-effects. We find that polling stations in panchayats controlled by the ruling party vote for its national candidate by an extra 1.5 to 1.8 percentage points. We then estimate the same equation within the sub-sample of polling locations that are water-stressed. Columns 3 and 4 show the estimates nearly double in these water-stressed locations. By contrast, estimates restricted to polling locations that are not water-stressed (Columns 5 and 6) show no evidence of a discontinuity. The bottom panel of Figure 3 visualizes the difference in ruling party vote shares in water-stressed and non-stressed areas. Comparing the top and bottom panels shows that the discrete jump in NREGA allocations at the cutoff is mirrored by an equally stark jump in the ruling party's vote share.

Are the differences between water-stressed and non-stressed areas statistically significant? Using 1000 clustered bootstrap replications we show that the difference between the estimates in Columns 4 and 6, our most precise specifications, are significant for both NREGA allocations (at the 10 percent level) and for the ruling party vote share (at the 5 percent level).

At the very least, these estimates imply the misallocation of poverty relief is especially grave in areas that most need assistance. Areas suffering water stress, where the local council is controlled by the ruling party, receive substantially more aid than equally desperate areas controlled by the opposition. The fact that subsequent election outcomes mirror that pattern is consistent with our hypothesis that having control of these resources yields especially large political gains for the ruling party among households in economic distress induced by water shortages.

One natural concern is that our measure of being water-stressed may be correlated with any number of confounding factors that might actually be driving the results. Areas where farmers must drill especially deep might also be areas that are historically more remote, geographically unusual, or more favorable to the ruling party for reasons unrelated to groundwater.

To alleviate these concerns we exploit a technological quirk in pumping technology that creates plausibly exogenous variation in access to groundwater. Beyond the depth of 8 meters below ground level, traditional centrifugal pumps cease to work effectively, due to changes in the atmospheric pressure at that depth. Indeed, to drill deeper in order to access water is considerably more expensive beyond 8 meters, providing a discontinuity in extraction cost at that level. This discontinuity at the depth of 8 meters has been used in previous research as exogenous variation in groundwater levels to show effects on poverty (Sekhri, 2014), violence (Sekhri and Hossain, 2020) and firm productivity (Liu and Sekhri, 2021).

We follow these studies and redefine "water-stressed" to mean a water depth greater than or equal to 8 meters below the surface, and restrict observations to panchayats with a depth within a window of 3 meters above and below the 8 meter cutoff. We then further restrict to "water-stressed" and estimate Equation 1 (now on panchayats with water depths of 8 to 11 meters). Comparing wells narrowly above and below this threshold of 8 meters allows us to overcome potential concerns of confounding factors affecting our observed outcomes, as well as being correlated with water depth. Columns 1 and 2 of Table 2 shows that the estimates are comparable or even larger than those in Columns 3 and 4 of Table 1A. Panchayats in areas that are water-stressed (those with depths just greater than the 8 meter cutoff) receive an extra 3 to 4 days per household of NREGA labor if they are controlled by the ruling party. In non-stressed areas, by contrast, there is no significant difference in the average NREGA allocation to places that are or are not controlled by the ruling party.

Columns 5—8 take a similar approach estimating Equation 2. The results are consistent with 1B. Columns 5 and 6 show that restricting to "water-stressed" polling locations (those with water depths of 8 to 11 meters) yields estimates even larger than those in Columns 3 and 4 of Table 1B. By contrast, Columns 7 and 8 show that restricting to "non-stressed" areas (polling locations of water depth 5 to 8 meters) yields estimates close to zero.

Figure 4 shows that the choice of 3 meters for the window around the 8 meter cutoff is not pivotal. We redo the estimates used to construct Table 2 using every window from ± 1 meter around the cutoff to ± 8 meters around the cutoff, always taking depths greater than 8 meters as our measure for whether the area is water-stressed. The results confirm that the results qualitatively robust to the the choice of window.

One last concern is that the apparent favoritism towards AITC-controlled panchayats is explained not by targeted spending or clientelism, but by co-partisan efficiencies. Under this hypothesis, AITC councils are better able to get projects approved through NREGA because the state government can pressure them to do the needed administrative work, or because the informal ties between local and state officials of the same party minimize information frictions in the approval process. While it is not possible to experimentally shut off any potential efficiency channel, one test of this hypothesis is to look at the targeting of NREGA jobs across villages within a panchayat.

Each panchayat is divided into several villages (as many as 20 in West Bengal). Since all of these villages are administered by the same council, differences in allocations within the panchayat are unlikely to arise from co-partisan efficiencies. In Appendix A.7 we estimate difference-in-discontinuity specifications to show that within a panchayat controlled by the AITC, villages that have supported the party in the prior two elections get more jobs. There is also some suggestive evidence that the difference is bigger in water-stressed areas, though the difference is not statistically significant (possibly because we are cutting the sample in too many ways). Regardless, it is hard to explain these differences in within-panchayat targeting as co-partisan efficiencies. Though we cannot completely rule out some role for such efficiencies, it is unlikely to be the sole explanation for our results.

6 Discussion and Directions for Future Research

Taken together our results suggest that politicians who can use public funds for partisan advantage will strategically target areas in hardship, and the resulting electoral impact is magnified. One caveat to our results is that since we rely on administrative data, we cannot directly observe whether the mechanism is an actual quid pro quo with voters, or merely gratitude for ruling party officials that deliver aid. Though the second scenario might seem more benign, its counterpoint is that voters blame an opposition official who cannot deliver critical aid because she is sabotaged by the state government. Nevertheless, one priority for future work is exploring which of these two scenarios is the true mechanism.

Another caveat to our results is that, like any result identified from a regression discontinuity, our estimates are only neighborhood average effects. One may wonder whether the selective targeting of NREGA funds would look similar farther away from the cutoff in areas that are are less competitive and more likely to be ruling party strongholds. Under our proposed mechanism, that the state government allocates funds to local politicians to help them raise votes for national candidates (Shenoy and Zimmermann, 2022), the answer is yes. Even within a ruling party stronghold the local politicians may need NREGA funds to turn out their voters for the party's national candidate. Figure 3 is consistent with that prediction. There is little evidence that areas far to the right of the cutoff receive substantially fewer NREGA benefits than those closer to the cutoff. Nevertheless, future research must consider whether the competitiveness of the political environment dampens or amplifies the incentive for political targeting.

This paper complements the results in Bobonis et al. (2022), which demonstrate that the demand for clientelism falls in response to an exogenous decrease in water stress created by an experiment that randomly allocated water cisterns to drought-hit households. Our results are consistent with the converse hypothesis that in the presence of water-stress, politicians reap electoral payoffs by targeting antipoverty funds—a possible increase in the "supply" of targeting or clientelism.

One especially troubling implication of our results is that politicians may view scarcity less as a problem to prevent than an opportunity to cement their grip on power (Wade, 1982). Prior work has found that voters evaluate the incumbent in part on how they respond to disasters (Cole et al., 2012; Tarquinio, 2021). But unlike a natural disaster, water scarcity is preventable through better infrastructure and more careful oversight of water use. One possible implication of our results is that politicians have no clear incentives to prevent such long-term scarcity because it enhances their power to dispense aid in return for votes. Indeed, many of the other maneuvers used by politicians to win elections, such as dispensing cheap electricity to power water pumps just before elections (Baskaran et al., 2015), are likely to aggravate the problem. Future work must explore whether forward-looking politicians distort their investments to keep voters ever-vulnerable to water-scarcity and thus ever-grateful for government aid.

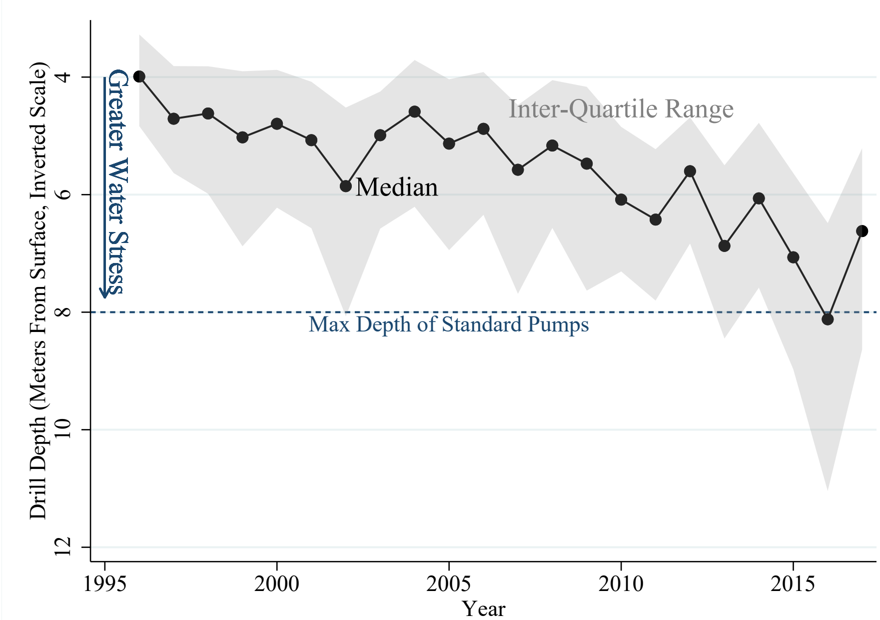
7 Tables and Figures

Figure 1

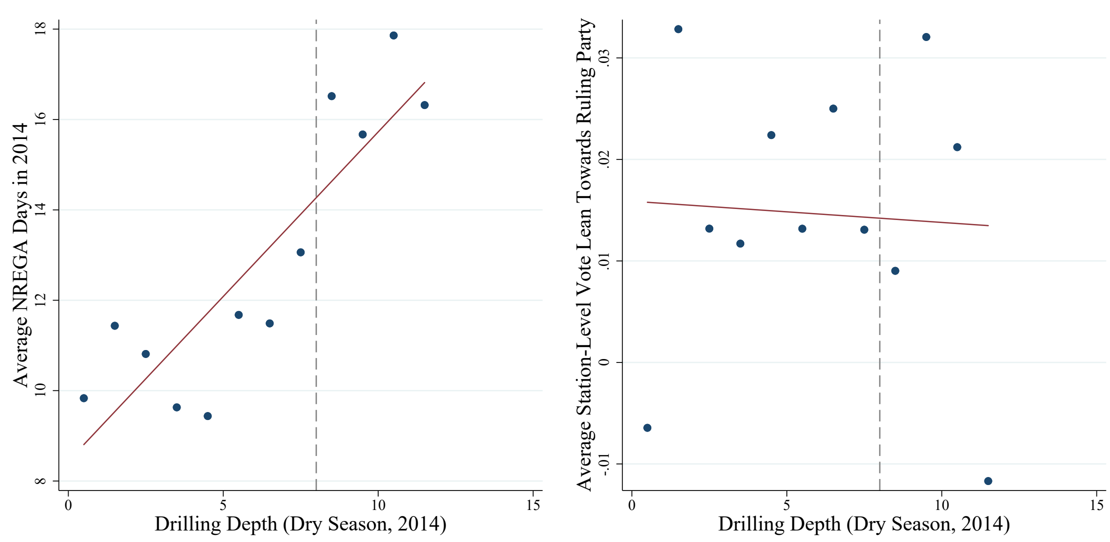
Water Tables Have Been Declining for Decades

Higher Aid but No Higher Ruling Party Representation in Drier Regions

A. Water Tables Declining to Critical Levels

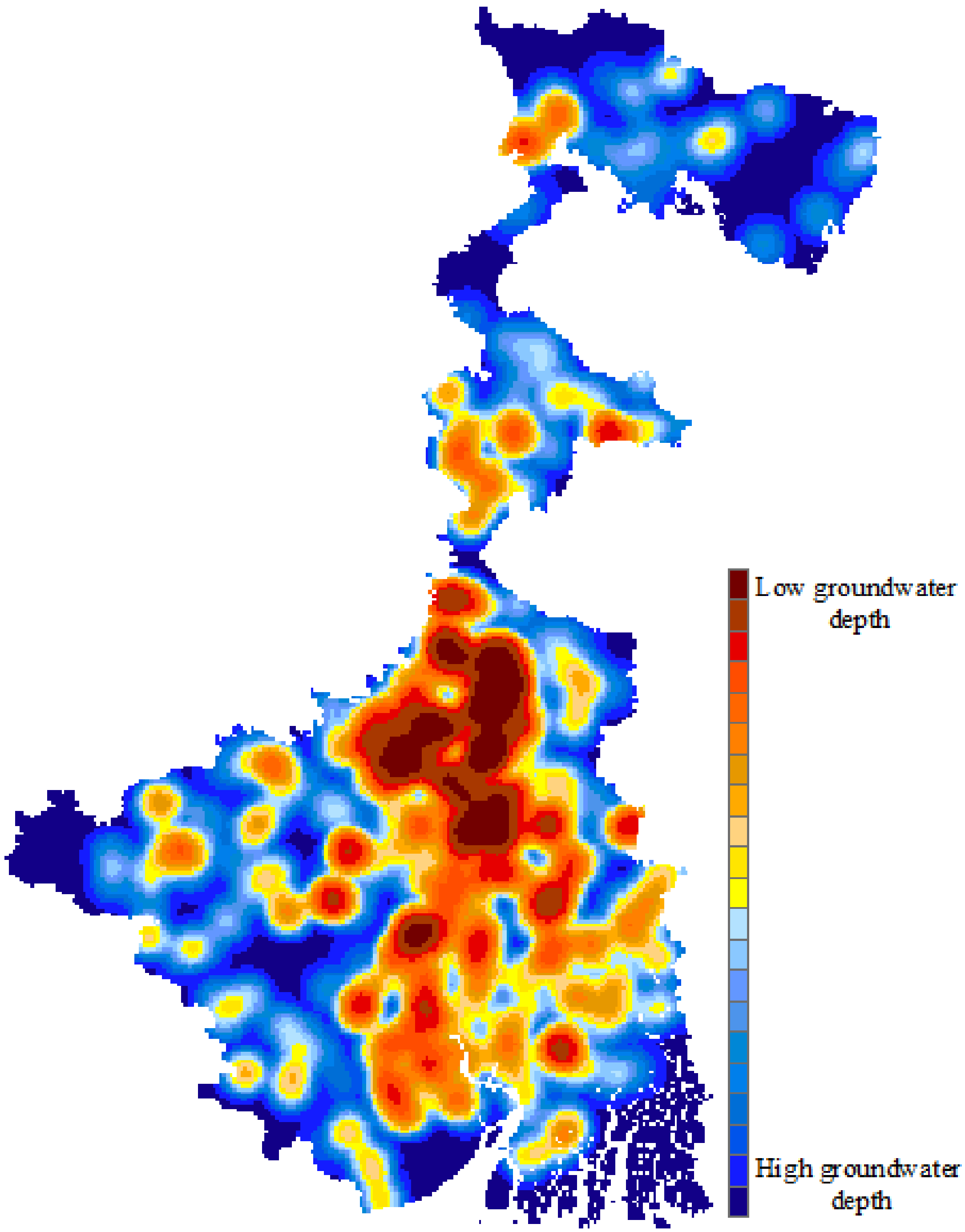


B. No Clear Political Correlations between Drier Regions and Ruling Party



Note: Figure A plots the percentiles of the distribution of groundwater depth (from the Central Groundwater Board) among polling locations in our sample from 1996 to 2016. Note that "depth" refers to how far below the surface a farmer must drill to access the water—greater depth implies the water table is more depleted. The inter-quartile range declines in tandem with the median, but there is great heterogeneity across polling location. While several individual wells already have a depth greater than 8 meters before the 2000s, it is striking that the median depth has steadily reached this value by 2016. This could be predictive of a significant water crisis in the near future, as pumping water rises steeply in cost. Figure B shows two plots that (i) track the amount of aid (NREGA days) being directed to regions by groundwater levels and (ii) the representation of the ruling party across regions with varying groundwater levels. While more aid predictably goes to drier areas, there is no pattern that emerges linking ruling party presence with groundwater depth.

Figure 2
Areas within the state of West Bengal with water stress (darker areas)

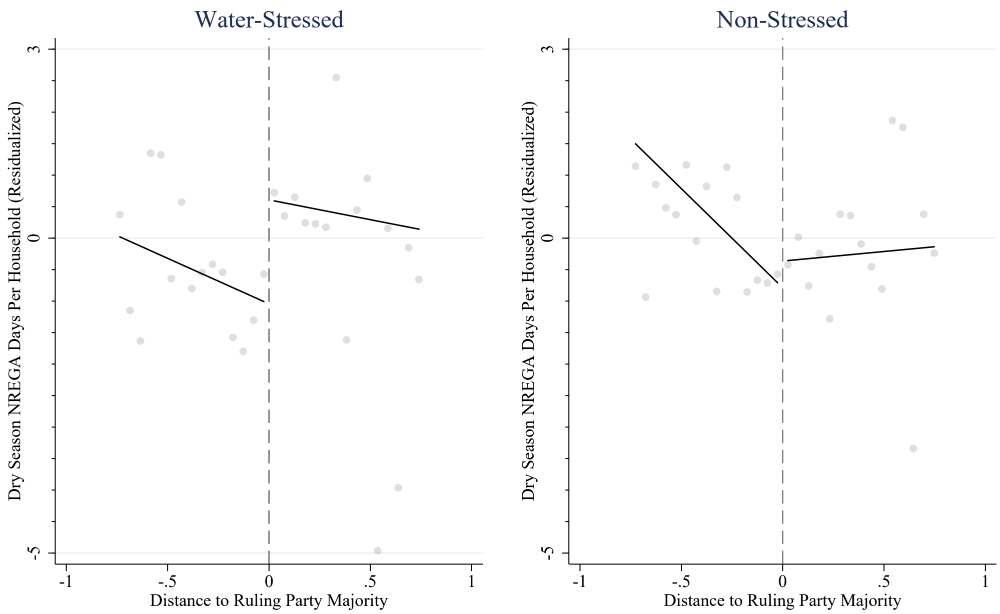


Note:
This figure shows the variation in groundwater levels across the state of West Bengal with blue referring to high water levels, transition to yellow and then red, as they go lower.

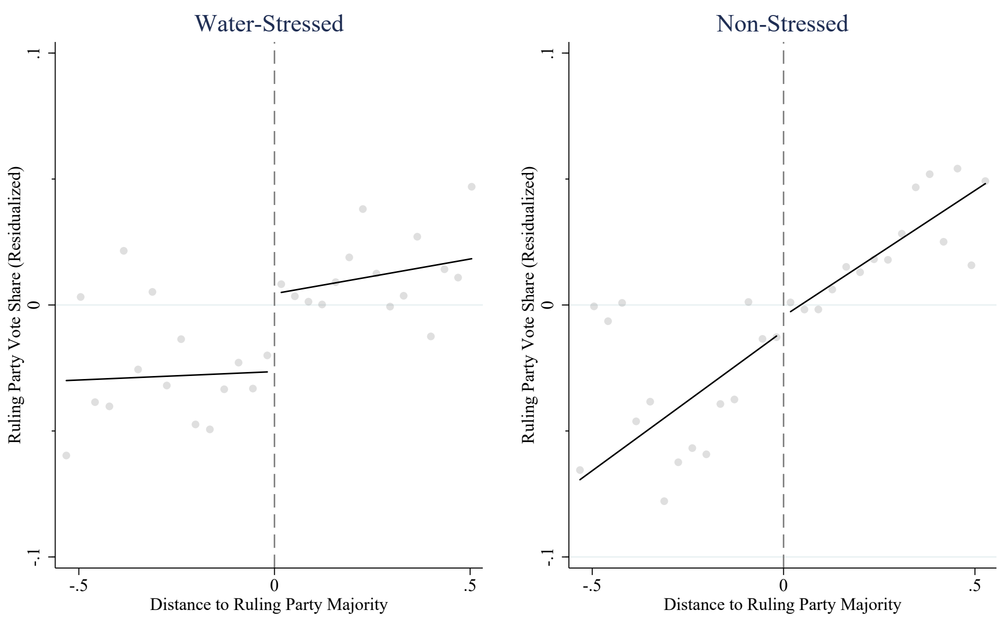
Figure 3

There is a Discontinuity in Vote Shares only in Water-Stressed Areas

A. Per-Household NREGA Days (Dry Season)

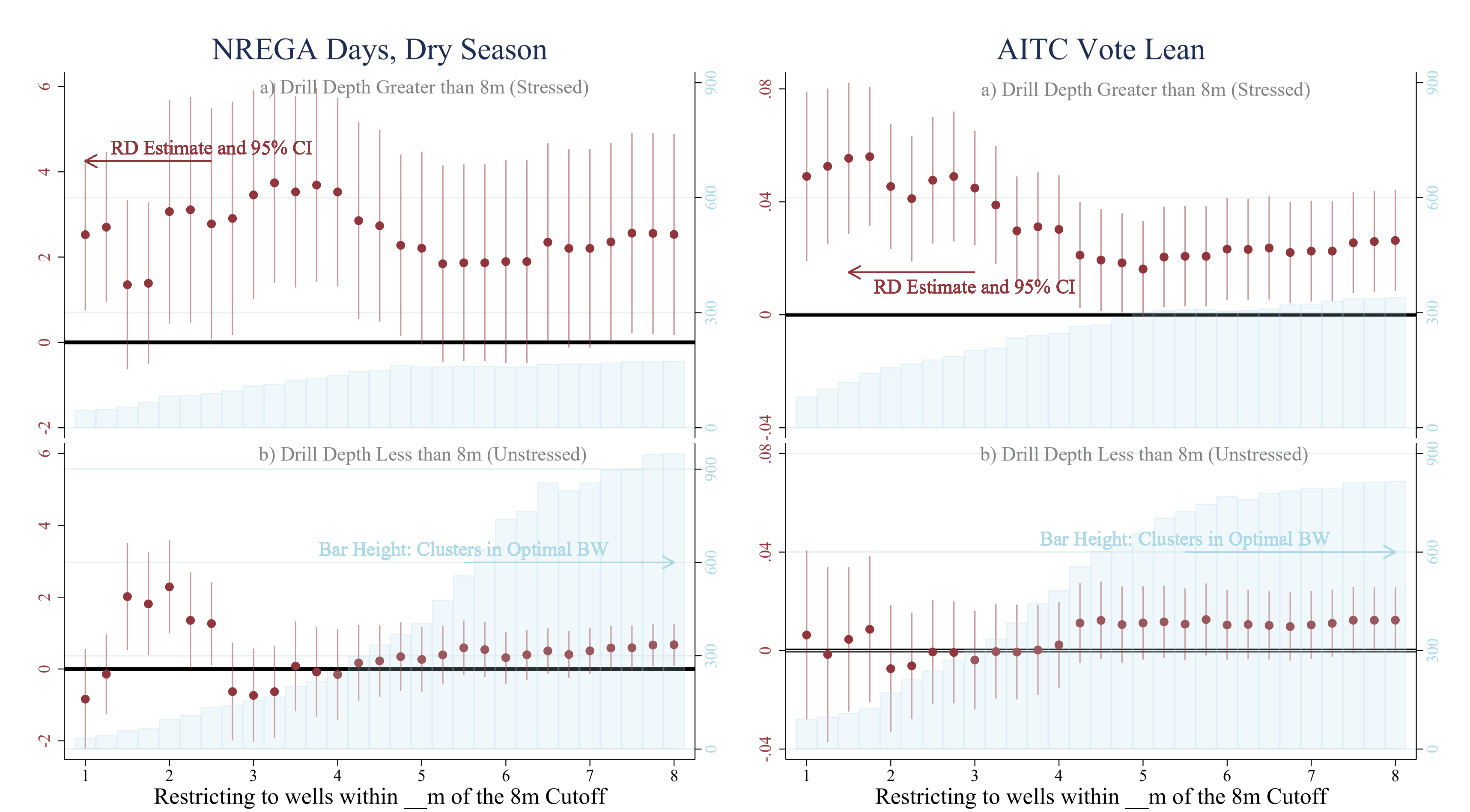


B. Ruling Party Vote Share



Note: This figure shows that the discontinuities in NREGA allocations and national vote share arise primarily in areas that are water-stressed. Each dot is the mean of the outcome within an equally-sized bin of the running variable. This figure defines “water-stressed” the same way as Table 1: panchayats or polling locations where depth one must drill to find water exceeds the median in our sample.

Figure 4
The Effect Sizes are Similar Even When Comparing Areas
with Depths Just Above and Below the 8 Meter Cutoff



Note: We test the sensitivity of the estimates in Table 2 to the window of observations above and below the 8 meter cutoff. Each point shows an RD estimate after restricting the full sample to polling locations with a drilling depth of $8 \pm x$, where x is varied along the horizontal axis. The top- and bottom-left panels are comparable to the specification in Columns 2 and 4, while the top- and bottom-right panels are comparable to Columns 6 and 8. The red points and lines show the estimate and 95 percent confidence interval. The heights the blue bars show the number of clusters used to estimate the coefficient (which declines as the window of drilling depths shrinks).

Table 1
Main Results

A. Panchayat-Level Average NREGA Days of Labor (Pooled)

	Full Sample		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.979***	1.068***	1.503***	1.766***	0.639	0.530
	(0.354)	(0.292)	(0.549)	(0.488)	(0.459)	(0.373)
Total Obs	5877	5877	2928	2928	2928	2928
Obs in BW	4200	4200	1926	1926	2046	2046
Clusters in BW	1400	1400	642	642	682	682
Control Mean	7.83	7.83	8.94	8.94	6.71	6.71
Bandwidth	0.775	0.775	0.773	0.773	0.482	0.482
Robust p-val	0.008	0.015	0.018	0.020	0.180	0.279
District FEs		X		X		X
Constituency FEs		X		X		X

B. Station-Level Ruling Party Vote Share

	Full Sample		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.015**	0.018***	0.029***	0.030***	0.001	0.007
	(0.006)	(0.005)	(0.008)	(0.006)	(0.009)	(0.007)
Total Obs	16580	16580	8168	8168	8171	8171
Obs in BW	10909	10909	5218	5218	5516	5516
Clusters in BW	1308	1308	674	674	821	821
Bandwidth	0.551	0.551	0.816	0.816	0.413	0.413
Robust p-val	0.030	0.035	0.001	0.001	0.917	0.326
District FEs		X		X		X
Constituency FEs		X		X		X

Note: We mark a panchayat or polling location as "water-stressed" if the depth one must drill to find water exceeds the median in our sample. The RD estimate gives the impact of having a local council with a narrow majority for the ruling party. Bandwidths are MSE-optimal (see Calonico et al., 2014). "Robust p-val" gives the p-value after adjusting for bandwidth uncertainty. See text for description of each specification.
*p=0.10 **p=0.05 ***p=0.01

Table 2

Results Hold Using the 8-Meter Depth Cutoff as the Measure of Water-Stress
Restricted to Wells 8 ± 3 Meters of Drilling Depth

	Water-Stressed		Non-Stressed		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NREGA	NREGA	NREGA	NREGA	Votes	Votes	Votes	Votes
RD Estimate	3.715**	3.458***	-1.124	-0.736	0.039***	0.045***	-0.006	-0.004
	(1.462)	(1.251)	(0.969)	(0.665)	(0.012)	(0.010)	(0.013)	(0.010)
Total Obs	486	486	732	732	1448	1448	2140	2140
Obs in BW	330	330	474	474	940	940	1404	1404
Clusters in BW	110	110	158	158	203	203	303	303
Control Mean	8.48	8.48	9.05	9.05	-0.03	-0.03	0.02	0.02
Bandwidth	1.585	1.585	0.580	0.580	1.250	1.250	0.437	0.437
Robust p-val	0.111	0.039	0.202	0.098	0.007	0.000	0.636	0.477
District FEs		X		X		X		X
Constituency FEs		X		X		X		X

Note: This table presents estimates of Equations 1 and 2 that define water-stress using the 8 meters threshold from Sekhri (2014). This table restricts the sample to panchayats and polling stations within 3 meters of the cutoff, but Figure 4 shows that the results are robust to other choices. The interpretation of the coefficients is similar to Table 1. See text for description of each specification.
*p=0.10 **p=0.05 ***p=0.01

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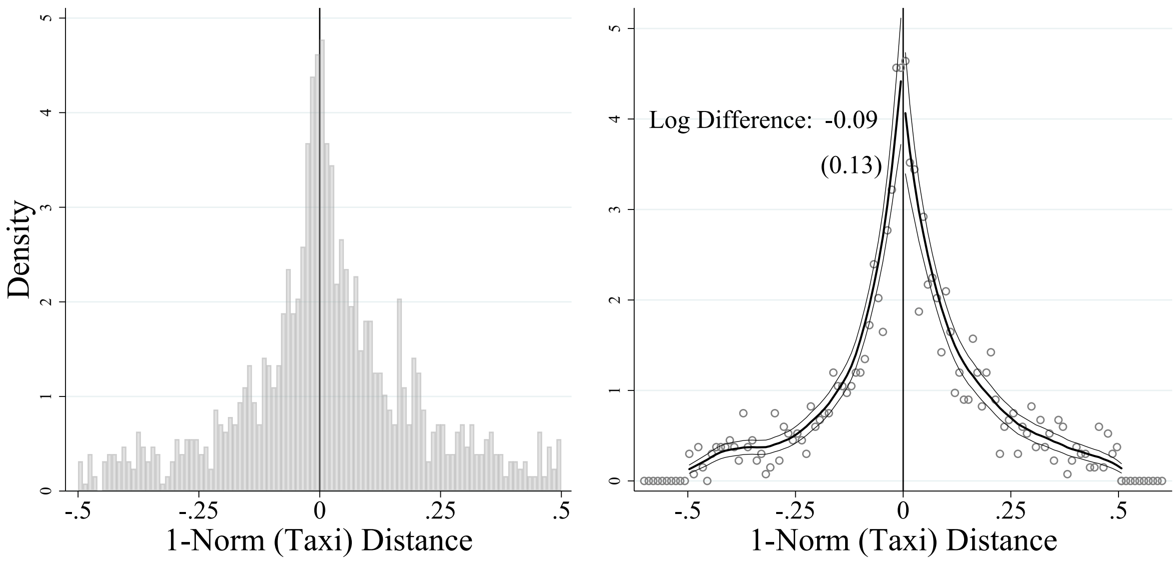
A Empirical Appendix

A.1 Density and Balance Tests: One-Norm Distance to AITC Majority

Figure 5

Density Checks



Note: We find no evidence of bunching in the running variable around the cutoff. We can therefore infer that there is no reason to believe that the elections themselves may be in any way manipulated.

Table 3
Balance Tests: Panchayat-Level

		Percentage of HHs...			
	(1)	(2)	(3)	(4)	(5)
	Total HHs	Landless Laborers	Non-Ag Business	Paying Income Tax	Destitute
RD Estimate	-219.685	-2.039*	0.146	0.094	0.088
	(188.611)	(1.113)	(0.161)	(0.481)	(0.069)
Total Obs	1917	1917	1917	1917	1917
Obs in BW	1243	1227	1279	1290	1341
Bandwidth	0.495	0.474	0.561	0.569	0.701
Robust p-val	0.239	0.108	0.339	0.823	0.171
Mean Left of Cutoff	5008.315	47.963	1.608	5.992	1.189

	Percentage of HHs with Salaried Job in...			Percentage of HHs with Monthly Income...		
	(1)	(2)	(3)	(4)	(5)	(6)
	Govt	Public	Private	Below 5k Rs	5k to 10k Rs	Over 10k Rs
RD Estimate	0.376	0.128	-0.112	-1.030	0.614	0.403
	(0.275)	(0.295)	(0.310)	(0.782)	(0.517)	(0.424)
Total Obs	1917	1917	1917	1917	1917	1917
Obs in BW	1341	1208	1218	1334	1334	1347
Bandwidth	0.700	0.446	0.461	0.679	0.680	0.724
Robust p-val	0.234	0.748	0.775	0.209	0.234	0.441
Mean Left of Cutoff	4.377	1.407	2.225	83.053	10.946	6.005

	Percentage of HHs Owning...			
	(1)	(2)	(3)	(4)
	Unirrigated Land	Irrigated Land	Other Land	2013 Avg. NREGA Days
RD Estimate	2.088	0.281	0.000	0.411
	(1.406)	(1.110)	(0.588)	(0.416)
Total Obs	1917	1917	1917	1959
Obs in BW	1203	1180	1228	1271
Bandwidth	0.439	0.411	0.474	0.493
Robust p-val	0.244	0.644	0.919	0.447
Mean Left of Cutoff	20.293	16.158	7.479	5.699

Note: We test for balance around the RD cutoff on a number of baseline characteristics across panchayats using data from the Socio-economic Caste Census of India. Only one coefficient is marginally significant, which is what one would expect to arise by chance under the null hypothesis of no imbalance. Even this coefficient, which implies the share of landless laborers is slightly lower in panchayats controlled by the ruling party, actually cuts against our main results. Landless laborers are some of the largest beneficiaries of NREGA aid, and yet we find a significantly larger proportion of aid directed to ruling party-aligned panchayats.
*p=0.10 **p=0.05 ***p=0.01

Table 4
Balance Tests: Polling Location-Level

	(1) 2011 AITC Vote Share	(2) 2009 AITC Vote Share	(3) 2013 Dry Season Drill Depth	(4) 2014 Dry Season Drill Depth
RD Estimate	0.023	-0.003	0.078	0.087
	(0.015)	(0.021)	(0.201)	(0.205)
Total Obs	11720	11730	16342	16342
Obs in BW	7854	7501	10726	10302
Clusters in BW	1261	1198	1306	1250
Bandwidth	0.545	0.445	0.555	0.467
Robust p-val	0.172	0.778	0.593	0.594
Mean Left of Cutoff	0.434	0.393	6.896	6.184

Note: This table tests for around the RD cutoff using outcomes measured by polling location. Columns 1 and 2 show there were no discontinuities in the AITC vote share in previous elections (using polling-station level data from the 2009 national election and the 2011 state election). Columns 3 and 4 show there are no baseline discontinuities in water levels in election years.
*p=0.10 **p=0.05 ***p=0.01

A.2 Panchayat-Level Impact on Vote Shares

Table 5
Impact on Vote Shares: Panchayat-Level

	Full Sample		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.017***	0.021***	0.033***	0.028***	0.007	0.012*
	(0.006)	(0.005)	(0.008)	(0.007)	(0.008)	(0.007)
Total Obs	1959	1959	976	976	976	976
Obs in BW	1263	1263	647	647	675	675
Bandwidth	0.480	0.480	0.853	0.853	0.446	0.446
Robust p-val	0.010	0.002	0.000	0.005	0.519	0.190
District FEs		X		X		X
Constituency FEs		X		X		X

Note: This table is analogous to Table 1.A, but vote shares and well depths are aggregated to the level of the panchayat. The outcome is the share of votes received by the AITC's candidate for parliament in the 2014 election (relative to the candidate's share in the parliamentary constituency). The share is calculated based on all votes from all polling stations in the panchayat. We take the median depth of all polling stations in the panchayat and define a panchayat as "water-stressed" if that measure is above the median among all panchayats. Standard errors are calculated using the three nearest neighbors.
*p=0.10 **p=0.05 ***p=0.01

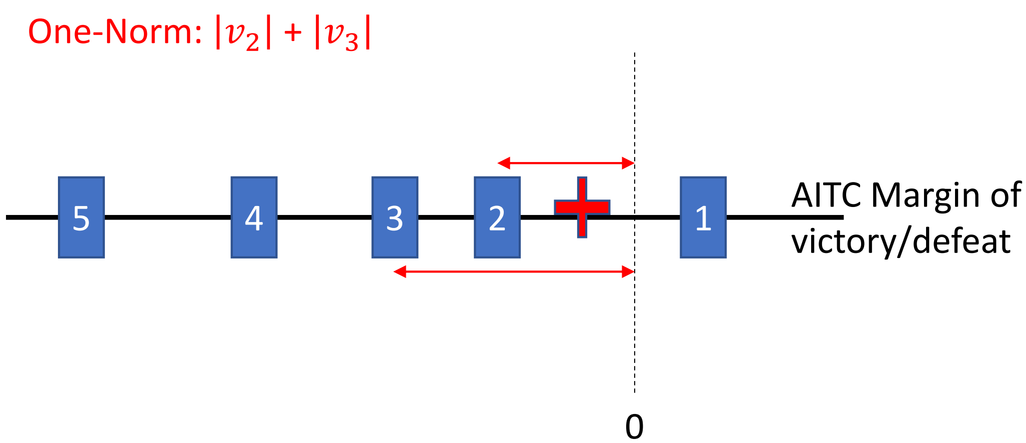
A.3 Defining the Running Variable, Continued

The p-norm is defined as

$$D_p(x, y) = \left[\sum_j |x_j - y_j|^p \right]^{1/p}$$

We define the running variable for panchayat i as the distance, as measured under the p-norm, between the election outcome in i and the closest outcome (of all seats) where the AITC holds an absolute majority. Figure 6 shows how the one-norm would be calculated for an outcome where the AITC loses four seats in a five-seat council.

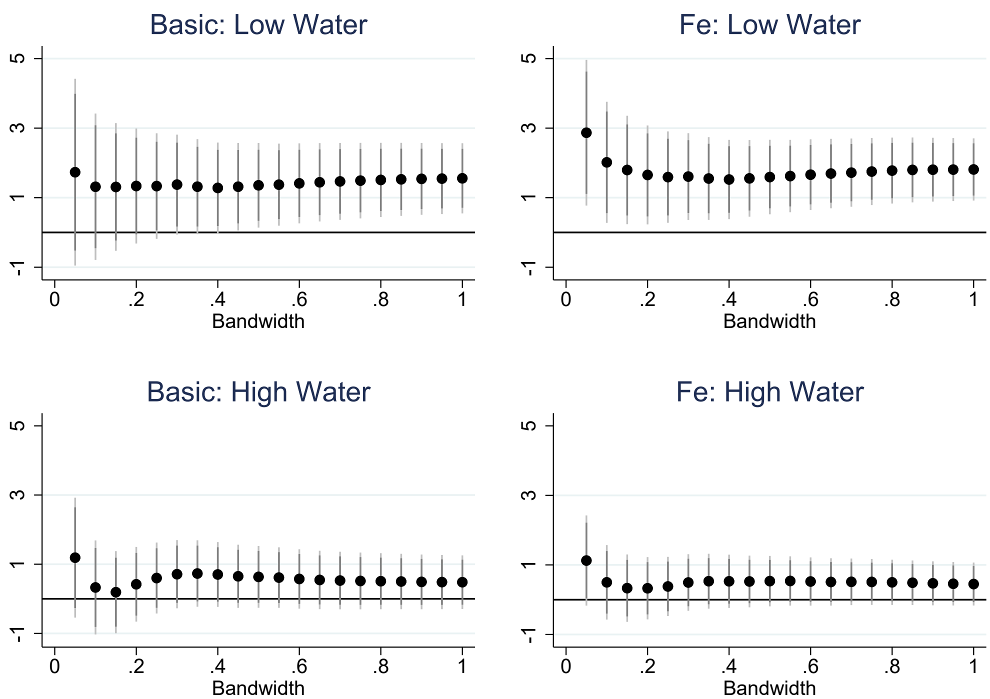
Figure 6
Visualization of one-norm taxi metric



Note: This figure shows the metric calculation for the case where AITC wins one ward in the village and is defeated in the others. The distance of each ward from the cutoff tells us the difference in vote share procured by the AITC candidate compared to their competitor. Given this scenario, the one-norm distance would be the absolute value of the distance between the AITC candidates in ward 2 and 3 and the best candidate: how much more they would need to win at least 3 wards, giving AITC a majority on this council.

A.4 Robustness to Choice of Bandwidth

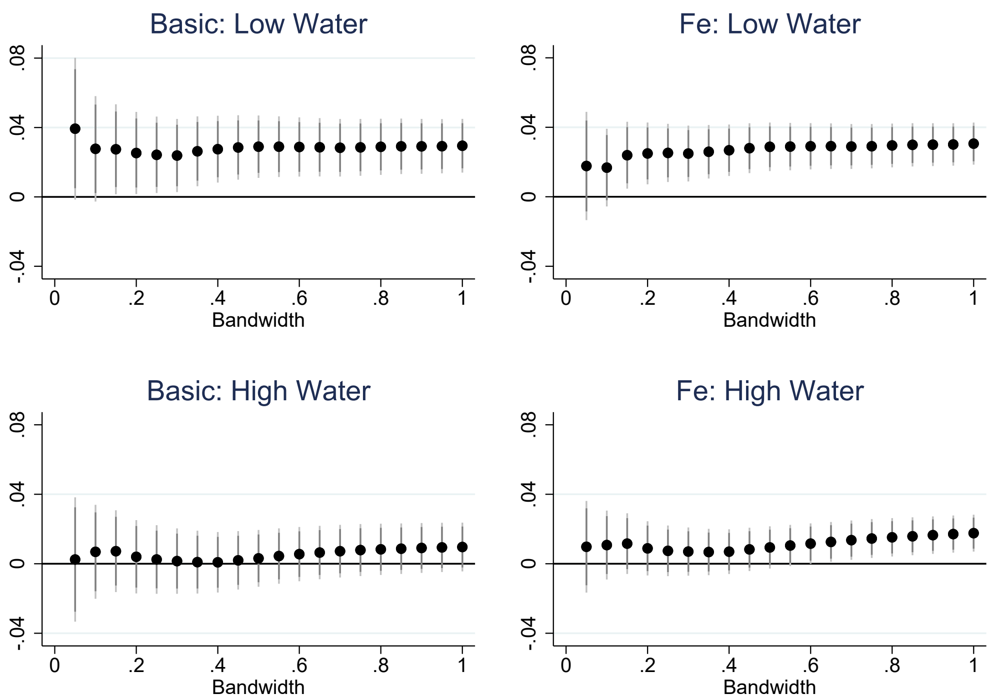
Figure 7
The Results are Robust to Choice of Bandwidth: NREGA Jobs



Note: Each point re-estimates the specifications in Columns 3—6 of Table 1A at a range of bandwidths. "Low Water" refers to the sub-sample of water-stressed panchayats, and "High Water" to the rest of the sample. "Basic" is the baseline specification in Columns 3 and 5, while "Fe" is the specification with fixed-effects in Columns 4 and 6. The black dot shows the point estimate, the dark gray line the 90 percent confidence interval, and the light gray line the 95 percent confidence interval.

Figure 8

The Results are Robust to Choice of Bandwidth: Vote Shares



Note: Each point re-estimates the specifications in Columns 3—6 of Table 1B at a range of bandwidths. "Low Water" refers to the sub-sample of water-stressed panchayats, and "High Water" to the rest of the sample. "Basic" is the baseline specification in Columns 3 and 5, while "Fe" is the specification with fixed-effects in Columns 4 and 6. The black dot shows the point estimate, the dark gray line the 90 percent confidence interval, and the light gray line the 95 percent confidence interval.

A.5 Robustness to Choice of Distance Metric

Table 6

Results in Table 1 Using the 2-Norm

Station-Level Ruling Party Vote Share

	Full Sample		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.013*	0.013**	0.029***	0.027***	0.000	0.004
	(0.007)	(0.006)	(0.009)	(0.007)	(0.010)	(0.007)
Total Obs	16580	16580	8168	8168	8171	8171
Obs in BW	10299	10299	5017	5017	5358	5358
Clusters in BW	1229	1229	1357	1357	1186	1186
Bandwidth	0.224	0.224	0.312	0.312	0.205	0.205
Robust p-val	0.148	0.060	0.006	0.023	0.888	0.271
Metric	2-Norm	2-Norm	2-Norm	2-Norm	2-Norm	2-Norm
District FEs		X		X		X
Constituency FEs		X		X		X

Panchayat-Level Average NREGA Days of Labor (Pooled)

	Full Sample		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	1.032**	1.111***	1.464**	1.812***	0.778	0.661
	(0.425)	(0.348)	(0.639)	(0.561)	(0.523)	(0.434)
Total Obs	5877	5877	2928	2928	2928	2928
Obs in BW	3963	3963	1875	1875	1887	1887
Clusters in BW	1321	1321	625	625	629	629
Control Mean	7.56	7.56	9.21	9.21	6.19	6.19
Bandwidth	0.282	0.282	0.325	0.325	0.198	0.198
Robust p-val	0.028	0.031	0.063	0.045	0.135	0.336
Metric	2-Norm	2-Norm	2-Norm	2-Norm	2-Norm	2-Norm
District FEs		X		X		X
Constituency FEs		X		X		X

Note: This table estimates specifications identical to those in Table 1 except that we use the 2-Norm distance metric instead of the 1-Norm as the running variable.

*p=0.10 **p=0.05 ***p=0.01

Table 7
Results in Table 1 Using the Infinity-Norm

Station-Level Ruling Party Vote Share

	Full Sample		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.012	0.012*	0.026**	0.023***	0.001	0.004
	(0.009)	(0.007)	(0.011)	(0.009)	(0.011)	(0.008)
Total Obs	16580	16580	8168	8168	8171	8171
Obs in BW	9114	9114	4644	4644	5319	5319
Clusters in BW	1071	1071	1237	1237	1169	1169
Bandwidth	0.113	0.113	0.158	0.158	0.136	0.136
Robust p-val	0.252	0.145	0.063	0.094	0.993	0.365
Metric	Inf-Norm	Inf-Norm	Inf-Norm	Inf-Norm	Inf-Norm	Inf-Norm
District FEs		X		X		X
Constituency FEs		X		X		X

Panchayat-Level Average NREGA Days of Labor (Pooled)

	Full Sample		Water-Stressed		Non-Stressed	
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	1.065**	1.181***	1.508*	1.905***	0.732	0.746
	(0.476)	(0.387)	(0.776)	(0.666)	(0.576)	(0.476)
Total Obs	5877	5877	2928	2928	2928	2928
Obs in BW	3843	3843	1725	1725	1764	1764
Clusters in BW	1281	1281	575	575	588	588
Control Mean	7.73	7.73	9.59	9.59	6.13	6.13
Bandwidth	0.169	0.169	0.164	0.164	0.121	0.121
Robust p-val	0.047	0.033	0.114	0.049	0.250	0.111
Metric	Inf-Norm	Inf-Norm	Inf-Norm	Inf-Norm	Inf-Norm	Inf-Norm
District FEs		X		X		X
Constituency FEs		X		X		X

Note: This table estimates specifications identical to those in Table 1 except that we use the Infinity-Norm distance metric instead of the 1-Norm as the running variable.
*p=0.10 **p=0.05 ***p=0.01

A.6 Balance Around the 8 Meter Cutoff in Drilling Depth

Table 8
Outcomes from the 2011 Census are Similar on Either Side of the 8 Meter Cutoff in Drilling Depth

	(1) Households	(2) Population	(3) SC Pop	(4) ST Pop	(5) Road	(6) Primary Schools	(7) Private Schools	(8) Internet Cafe
RD Estimate	287.066	821.793	-33.122	-223.515	0.081	5.191**	-0.379	0.032
	(366.633)	(1487.546)	(652.602)	(291.247)	(0.057)	(2.278)	(0.249)	(0.031)
N	1476	1476	1476	1476	1472	1476	1476	1473
Obs in BW	298	354	290	163	396	141	362	316
Bandwidth	2.3	2.7	2.2	1.5	3.1	1.2	2.8	2.6
Robust p-val	0.438	0.571	0.742	0.432	0.223	0.021	0.181	0.378
Mean Left of Cutoff	4021.24	17907.40	4948.39	1258.25	0.18	16.82	0.53	0.07

Note: This table tests for differences in 2011 census outcomes around the 8 meter drill depth cutoff. The estimates are regression discontinuity coefficients based on a local linear regression with triangular weighted kernel and the optimal bandwidth calculated using the method of Calonico et al. (2014). The unit of observation is a panchayat, and the sample is restricted to the subset for which we are able to link to 2011 Census outcomes. The standard errors are based on the 3 nearest neighbors in the running variable.
*p=0.10 **p=0.05 ***p=0.01

A.7 Is it Co-Partisan Efficiencies?

Let v index a village within panchayat i, and let α_i denote a panchayat fixed-effect. Finally, let a_{iv} denote some proxy for how many AITC supporters live in village v. In practice, a_{iv} is the average of the AITC vote share in the 2011 state election and the 2013 local election. For these tests we focus on dry season labor in the year 2014 L_{iv}. We estimate the difference-in-discontinuities specification

$$L_{iv} = \alpha_i + \alpha_1 d_i a_v + \alpha_2 d_i a_v M_i + \beta a_v M_i + \varepsilon_{iv} \qquad \text{for } i \text{ such that } |d_i| < h \tag{3}$$

The direct effect of AITC control (as well as the controls, the running variable, and its interaction with AITC control) are absorbed into the panchayat fixed effect. The coefficient β is the difference-in-discontinuities between villages with high versus low numbers of AITC supporters. Intuitively, we are simultaneously estimating the size of the change in NREGA jobs for high-a and low-a when the running variable crosses the threshold, then calculating the difference.

Tables 9 and 10 estimate Equation 3 for the overall sample and the subsamples of water-stressed and non-stressed panchayats. Table 9 marks a panchayat as water-stressed if the drilling depth is above the median, while Table 10 uses the 8-meter cutoff definition.

Table 9 shows that the difference-in-discontinuities in the overall sample is positive. It remains positive when we restrict to the sub-sample where we have water data. Since the same council president administers all villages within a panchayat, it is hard to explain this result as a co-partisan efficiency. The AITC president is getting projects approved and disproportionately allocating the projects (or at least the jobs) to villages that have supported the party in prior elections.

Table 9 also shows that the difference-in-discontinuities is positive in both the water-stressed and non-stressed sub-samples. There is some suggestive evidence that the point estimate is bigger in the water-stressed sample, though the estimates are noisy enough to contain one another in their confidence intervals. One possibility is that the AITC targets political supports a matter of course. It allocates extra jobs to water-stressed panchayats, but all jobs are disproportionately targeted to supporters regardless of the overall number.

It is also possible that our basic definition of water-stressed is too strongly correlated with unobservables. Table 10 attempts the same test using the 8-meter cutoff. The estimates lose statistical significance—not surprising given how finely we are slicing the data—but the coefficient in the water-stressed sample remains large, while that in the non-stressed sample is close to zero.

The comparison of the stressed and non-stressed samples are at best suggestive—the estimates are far too noisy to take as definitive. But the estimates in the overall sample make it difficult to argue there is no political targeting, and that all of the results are purely explained by co-partisan efficiencies.

Table 9

Within-Panchayat Difference-in-Discontinuities: Basic Definition of Water-Stressed

	Full Sample	Subsample with Water Data		
	(1)	(2)	(3)	(4)
	All	All	Water-Stressed	Non-Stressed
Majority X AITC Support	5.022***	5.089***	5.275*	4.346**
	(1.938)	(1.942)	(2.964)	(2.159)
Obs in BW	11107	11084	5852	5870
Clusters	1323	1319	670	726
Bandwidth	0.588	0.585	0.995	0.658
Metric	1-Norm	1-Norm	1-Norm	1-Norm
Panchayat FEs	X	X	X	X

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table estimates a difference-in-discontinuities specification that tests whether, after controlling for panchayat fixed-effects, the size of the discontinuity in 2014 dry season NREGA allocations is bigger for villages within the panchayat that have historically voted for the AITC relative to villages that voted for other parties. The unit of observation is a village. A panchayat is defined as "water-stressed" based on whether it is above- or below-median in the drilling depth. The tests in Columns 2—4 are restricted to panchayats for which we have groundwater data. *p=0.10 **p=0.05 ***p=0.01

Table 10

Within-Panchayat Difference-in-Discontinuities: Definition Based on 8 Meter Cutoff

	Full Sample	Subsample with Water Depth 8m +/- 3m		
	(1)	(2)	(3)	(4)
	All	All	Water-Stressed	Non-Stressed
Majority X AITC Support	5.022***	1.782	3.295	0.239
	(1.938)	(4.219)	(6.812)	(4.269)
Obs in BW	11107	3032	1128	1998
Clusters	1323	352	135	230
Bandwidth	0.588	0.847	1.920	0.791
Metric	1-Norm	1-Norm	1-Norm	1-Norm
Panchayat FEs	X	X	X	X

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table is the same as Table 9, except a panchayat is defined as "water-stressed" if the drilling depth is greater than 8 meters. The tests in Columns 2—4 are restricted to panchayats with drilling depths within 3 meters of the 8 meter cutoff.
*p=0.10 **p=0.05 ***p=0.01