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

Meera Mahadevan†
Ajay Shenoy‡

February 1, 2022

Abstract

We study whether resource scarcity enhances the scope for clientelism 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 consequently 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

*We are grateful to Gaurav Khanna, Priya Mukherjee, Paul Niehaus, Nishith Prakash and Sheetal Sekhri for helpful comments. We thank Alexandra Nava and Kaylee Garcia for excellent research assistance. We thank the seminar participants at the University of California at Irvine for useful feedback. All views expressed in the paper and any errors are our own.

†University of California, Irvine; email at meera.m@uci.edu. Website: http://meeramahadevan.com. Postal Address: University of California, Irvine, Department of Economics, Social Science Plaza A (SSPA) 3139, Irvine CA, 92697

‡University of California, Santa Cruz; email at azshenoy@ucsc.edu. Phone: (831) 359-3389. Website: http://people.ucsc.edu/∼azshenoy. Postal Address: Rm. E2455, University of California, M/S Economics Department, 1156 High Street, Santa Cruz CA, 95064.

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 support a clientelistic machine?

This 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 clientelistic ruling party to buy or retain votes, particularly in developing countries, which may lack the institutional checks to resist clientelism even as they bear the greatest burden from climate change and resource shortages (Burgess et al., 2017, 2014; Carleton et al., 2020). But there is as yet no direct evidence showing that an exogenous shortage of resources causes parties to grow more clientelistic, or that their efforts 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 access without unaffordable drilling technology. During the dry months after the monsoon

[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)

harvest, many farmers rely on jobs provided through a public works program, 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 the regions that are drier and support for the ruling party (Panel B (ii)). Nevertheless, these drier areas receive a higher per-household allocation of NREGA labor (Panel B (i)). But local officials often serve as the frontline workers of the political machine (Shenoy and Zimmermann, 2020; Bussell, 2019). The state government has a strong incentive to channel funds through its co-partisans to help them maintain their networks of clients. 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 ruling party allocates disproportionate funds, and wins disproportionate votes, in water-stressed areas controlled by its allies. We derive variation in who controls the local government from close contests in the 2013 local council election. Different combinations of local victories affect the composition of the council and ultimately the party holding the majority. The outcome of each of these closely fought local elections is quasi-random, and each closely fought local victory can have a meaningful impact on the final composition of the larger council. Our regression discontinuity design leverages a multidimensional running variable constructed from seat-level vote shares. We leverage exogenous variation arising from a local council narrowly aligned with the ruling party of the state government. We then measure the impact of ruling party control over the local council on the aggregate number of jobs it receives, and the number of votes won from the same jurisdiction 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 imply 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 an unusually pernicious form of clientelism.

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, physical 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 without clientelistic motives, 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. Previous work has noted that *even within a panchayat*, areas that have historically supported the AITC get more jobs when the AITC gains an absolute majority (Shenoy and Zimmermann, 2020). And as we describe in Section 2, there is ample anecdotal and survey evidence that local politicians reward villagers for their votes on behalf of national political parties.

Our main contribution is to the literature on resource shortages and political control. While

[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.

there is a rich literature showing that resources shortages cause political instability (Blattman and Miguel, 2010; Carreri and Dube, 2017; Oeindrila and Vargas, 2013; Caselli et al., 2015), our findings show that the opposite is also possible. The ruling party may be able to strengthen its grip by exploiting resource shortages, concentrating power in the hands of incumbents. 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) but their relevance to increasing resource stress have not been previously examined.

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). A corollary of our results is that politicians may have little incentive to design policies to manage depleting water levels because they can exploit its scarcity for political power, a phenomenon alluded to in the context of underperforming canals in India by Wade (1982). 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 to exacerbating the hold that politicians have 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 scope for clientelism. 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 a world of scarcity, the power to withhold aid is ultimately the power to choose who goes hungry. It is no surprise that such power engenders political control.

2 Background and Natural Experiment

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.

[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.

[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 state.

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.

The connection between this 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 days of NREGA labor are allocated to each gram panchayat. The council president in turn controls how much of the panchayat's shelf of labor is allocated to each household (Government of India, 2013).

2.2 Clientelism and Antipoverty Programs

The federal structure of India's system lays the groundwork for clientelism. Local politicians use their gate-keeping power over antipoverty programs to build networks of followers, which they can 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

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

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 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 are the glue that binds these clientelistic networks, 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).[6]

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 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.

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.

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

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 (2020), 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.[7] 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.4 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.4 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). 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

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

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.

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 an extra 0.8 to 0.9 days of labor during the dry seasons of 2014 through 2016, a roughly 11 to 12 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 1.2 to 1.5 days of labor per household. Areas that are not water-stressed (Columns 5—6) receive a statistically insignificant 0.5 days of labor. This contrast is visualized in Figure 2, 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 2 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 2 to 3 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 3 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 choice of window has little bearing on the estimates. The RD estimate is large and significant in areas that are water-stressed, and small and insignificant elsewhere.

6 Discussion and Directions for Future Research

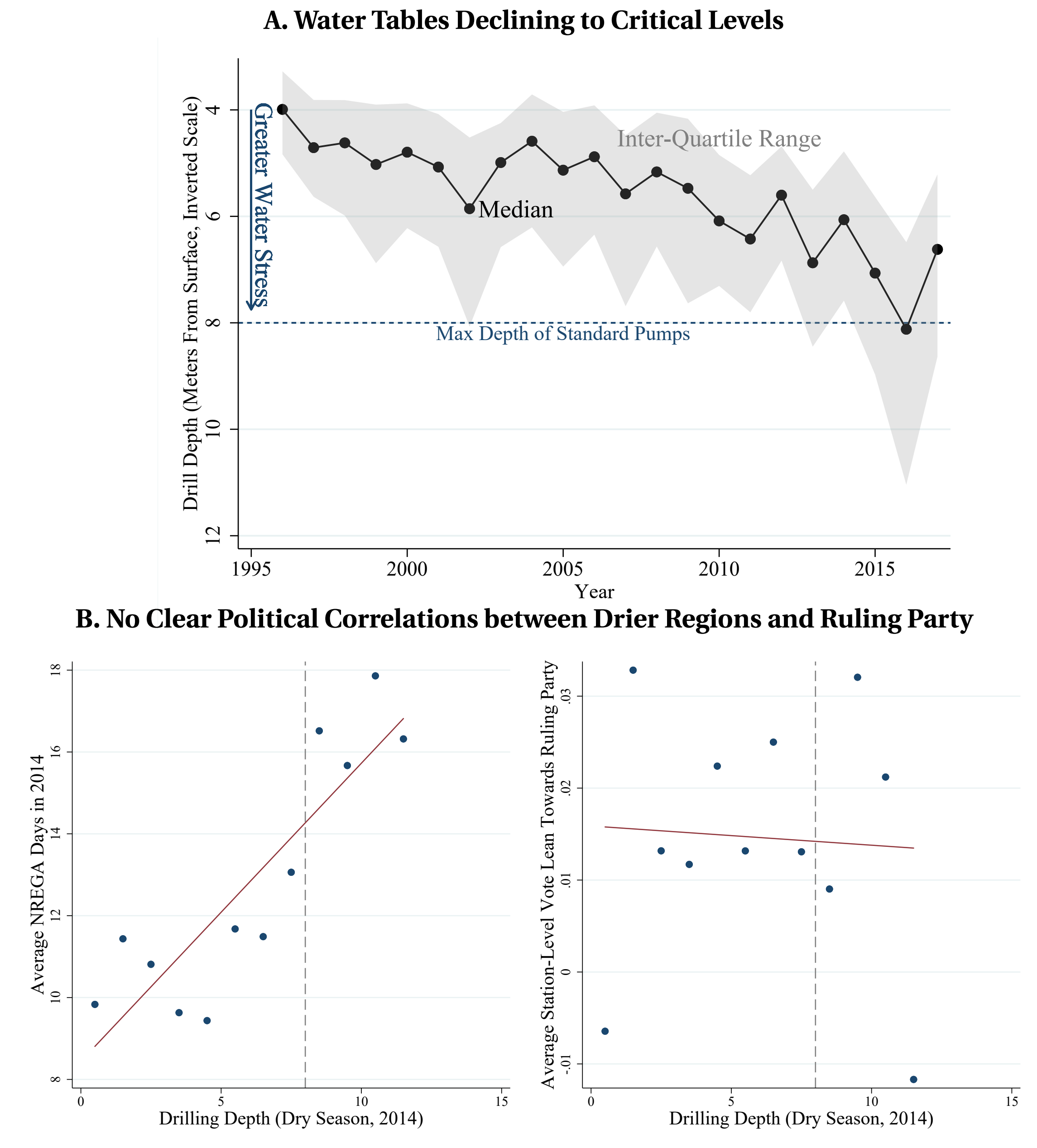
Taken together our results suggest that wherever politicians have the means to spend public funds for partisan advantage, the electoral impact is magnified in the presence of scarcity. One caveat to our results is that since we rely on administrative data, we cannot directly observe whether the mechanism 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.

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. But 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

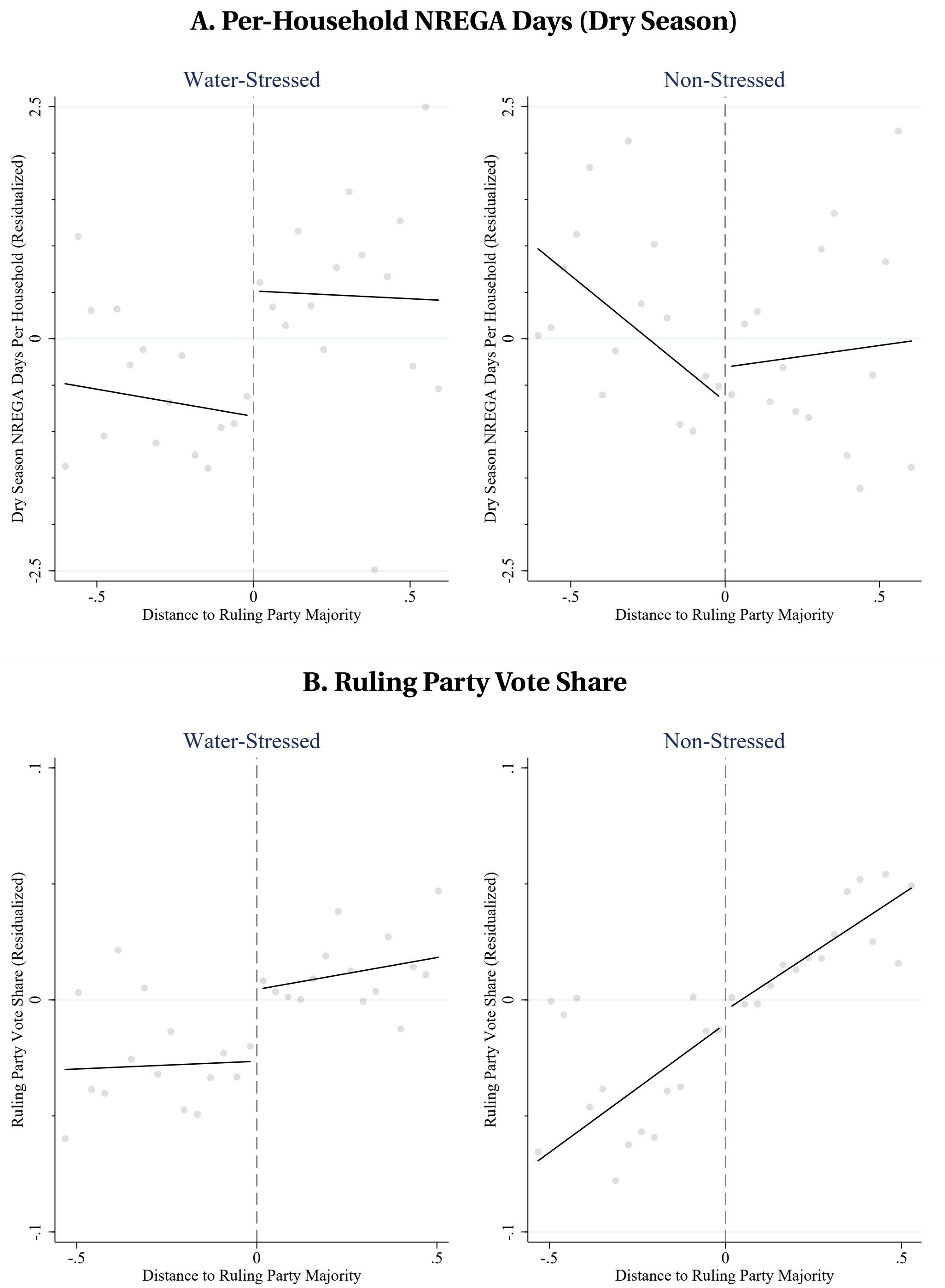
Water Tables Have Been Declining for Decades in West Bengal: No Ex-ante Evidence of Ruling Party Representation in Drier Regions



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.

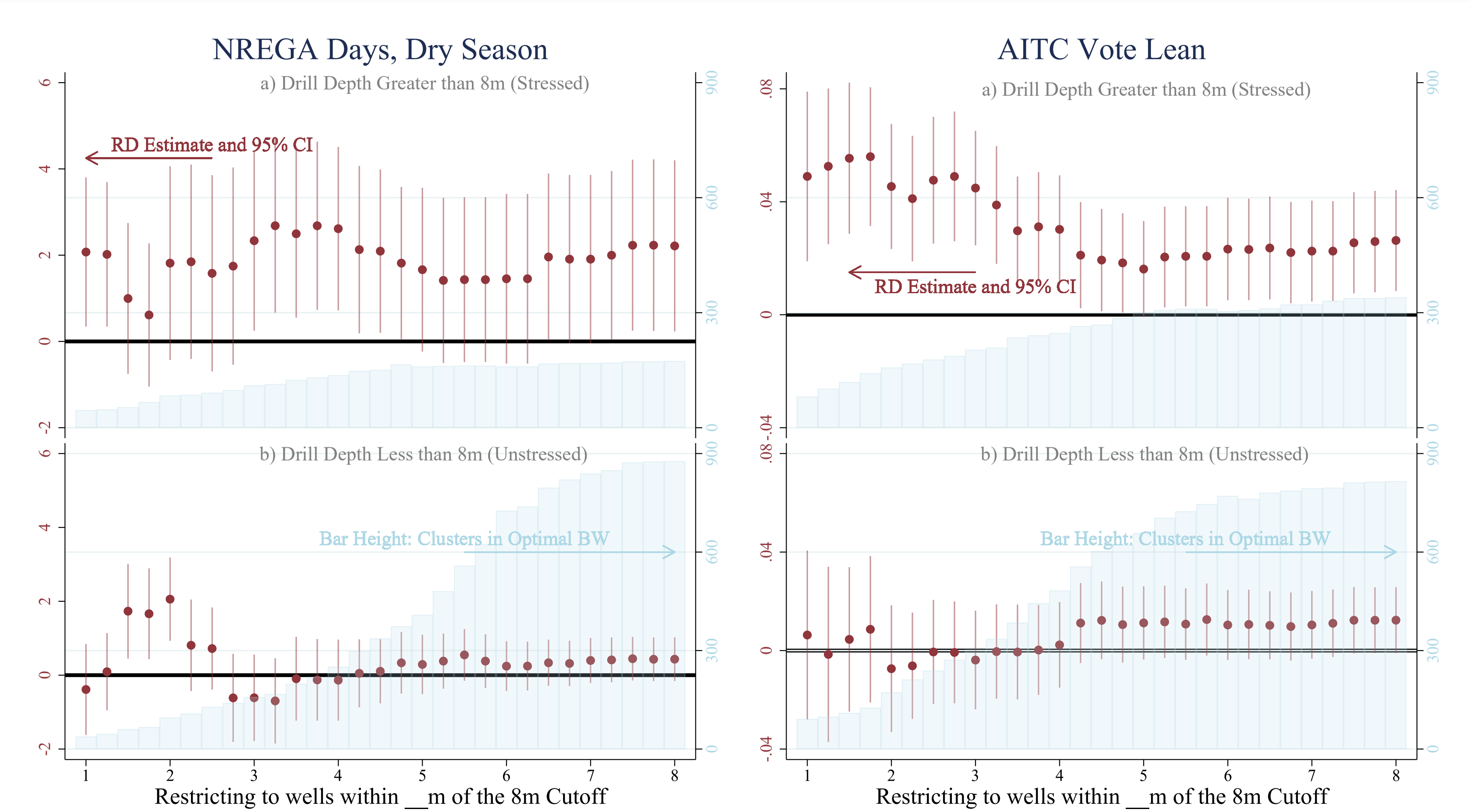
Figure 2

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



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 3
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	0.820**	0.887***	1.237**	1.551***	0.539	0.451
	(0.328)	(0.272)	(0.484)	(0.422)	(0.409)	(0.334)
Total Obs	7836	7836	3904	3904	3904	3904
Obs in BW	5376	5376	2568	2568	2816	2816
Clusters in BW	1344	1344	642	642	704	704
Control Mean	7.24	7.24	8.04	8.04	6.52	6.52
Bandwidth	0.629	0.629	0.769	0.769	0.552	0.552
Robust p-val	0.022	0.037	0.028	0.016	0.238	0.472
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 $\pm$ 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	2.984**	2.336**	-0.826	-0.612	0.039***	0.045***	-0.006	-0.004
	(1.259)	(1.066)	(0.865)	(0.596)	(0.012)	(0.010)	(0.013)	(0.010)
Total Obs	648	648	976	976	1448	1448	2140	2140
Obs in BW	440	440	632	632	940	940	1404	1404
Clusters in BW	110	110	158	158	203	203	303	303
Control Mean	8.13	8.13	8.10	8.10	-0.03	-0.03	0.02	0.02
Bandwidth	1.638	1.638	0.579	0.579	1.250	1.250	0.437	0.437
Robust p-val	0.128	0.093	0.273	0.108	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 3 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

References

Asher, Sam and Paul Novosad, "Politics and Local Economic Growth: Evidence from India," *American Economic Journal: Applied Economics*, 2017, *9* (1), 229–273.

Asoka, Akarsh, Tom Gleeson, Yoshihide Wada, and Vimal Mishra, "Relative Contribution of Monsoon Precipitation and Pumping to Changes in Groundwater Storage in India," *Nature Geoscience*, February 2017, *10* (2), 109–117.

Bardhan, Pranab and Dilip Mookherjee, "Clientelistic Politics and Economic Development: An Overview," in Jean-Marie Baland, François Borguignon, Jean-Philippe Platteau, and Thierry Verdier, eds., *The Handbook of Economic Development and Institutions*, Princeton and Oxford: Princeton University Press, 2020.

Baskaran, Thushyanthan, Brian Min, and Yogesh Uppal, "Election Cycles and Electricity Provision: Evidence from a Quasi-experiment with Indian Special Elections," *Journal of Public Economics*, 2015, *126*, 64–73.

Besley, Timothy and Robin Burgess, "The Political Economy of Government Responsiveness: Theory and Evidence from India," *Quarterly Journal of Economics*, 2002, *117* (4), 1415–1451.

Blattman, Christopher and Edward Miguel, "Civil War," *Journal of Economic Literature*, March 2010, *48* (1), 3–57.

Brender, Adi and Allan Drazen, "How Do Budget Deficits and Economic Growth Affect Reelection Prospects? Evidence from a Large Panel of Countries," *American Economic Review*, 2008, *98* (5), 2203–2220.

Burgess, Robin, Olivier Deschênes, Dave Donaldson, and Michael Greenstone, "The Unequal Effects of Weather and Climate Change: Evidence from Mortality in India," Working Paper, MIT 2014.

___ , ___ , ___ , and ___ , "Weather, Climate Change and Death in India," Working Paper, London School of Economics 2017.

Bussell, Jennifer, *Clients and Constituents: Political Responsiveness in Patronage Democracies*, New York: Oxford University Press, 2019.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik, "Robust Nonparametric Confidence Intervals for Regression-discontinuity Designs," *Econometrica*, 2014, *82* (6), 2295–

2326.

Carleton, Tamma A., Amir Jina, Michael T. Delgado, Michael Greenstone, Trevor Houser, Solomon M. Hsiang, Andrew Hultgren, Robert E. Kopp, Kelly E. McCusker, Ishan B. Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Jiacan Yuan Arvid Viaene, and Alice Tianbo Zhang, "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits," Working Paper 27599, National Bureau of Economic Research July 2020.

Carreri, Maria and Oeindrila Dube, "Do Natural Resources Influence Who Comes to Power, and How?," *The Journal of Politics*, 2017, *79* (2), 502–518.

Caselli, Francesco, Massimo Morelli, and Dominic Rohner, "The Geography of Interstate Resource Wars," *The Quarterly Journal of Economics*, 02 2015, *130* (1), 267–315.

Cattaneo, Matias D., Luke Keele, Rocío Titiunik, and Gonzalo Vazquez-Bare, "Interpreting Regression Discontinuity Designs with Multiple Cutoffs," *The Journal of Politics*, 2016, *78* (4), 1229–1248.

Cole, Shawn, "Fixing Market Failures or Fixing Elections? Agricultural Credit in India," *American Economic Journal: Applied Economics*, 2009, *1* (1), 219–250.

___ **, Andrew Healy, and Eric Werker**, "Do voters demand responsive governments? Evidence from Indian disaster relief," *Journal of Development Economics*, 2012, *97* (2), 167–181.

De la O, Ana, "Do Conditional Cash Transfers Affect Electoral Behavior? Evidence from a Randomized Experiment in Mexico," *American Journal of Political Science*, 2013, *57* (1), 1–14.

Desai, Sonalde and Reeve Vanneman, "India Human Development Survey-II (IHDS-II), 2011-12," *Inter-university Consortium for Political and Social Research*, August 2018.

Deschênes, Olivier and Michael Greenstone, "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, October 2011, *3* (4), 152–85.

Dey, Subhasish and Kunal Sen, "Is Partisan Alignment Electorally Rewarding? Evidence from Village Council Elections in India," 2016. IZA Discussion Paper No. 9994.

Dunning, Thad and Janhavi Nilekani, "Ethnic Quotas and Political Mobilization: Caste, Parties, and Distribution in Indian Village Councils," *American Political Science Review*, 2013, *107* (1), 35–56.

Feigenbaum, James J., Alexander Fouirnaies, and Andrew B. Hall, “The Majority-Party Disadvantage: Revising Theories of Legislative Organization,” *Quarterly Journal of Political Science*, 2017, *12* (3), 269–300.

Folke, Olle, “Shades of Brown and Green: Party Effects in Proportional Election Systems,” *Journal of the European Economic Association*, 2014, *12* (4), 1127–1422.

George, Siddharth Eapen and Dominic Ponattu, “Like Father, Like Son? The Effect of Political Dynasties on Economic Development,” *Working Paper*, 2020.

Gibson, Ulrich P. and Rexford D. Singer, “Small Wells Manual: Location, Design, Construction, Use and Maintenance,” Technical Report, Washington DC: Department of State Agency for International Development 1969.

Government of India, “Mahatma Gandhi National Rural Employment Guarantee Act, 2005 Operational Guidelines,” Technical Report, Ministry of Rural Development 2013. https://nrega.nic.in/Circular_Archive/archive/Operational_guidelines_4thEdition_eng_2013.pdf (accessed July 8, 2018).

Green, Timothy Richard, *Linking Climate Change and Groundwater*, Cham: Springer International Publishing,

Healy, Andrew and Gabriel S. Lenz, “Substituting the End for the Whole: Why Voters Respond Primarily to the Election-Year Economy,” *American Journal of Political Science*, 2014, *1* (58), 31–47.

___ **and Neil Malhotra**, “Retrospective Voting Reconsidered,” *Annual Review of Political Science*, 2013, *16*, 285–306.

Katakorpi, Kaisa, Panu Poutvaara, and Marko Tervio, “Returns to Office in National and Local Politics,” 2013. CESIFO Working Paper No. 4542.

Khanna, Gaurav and Priya Mukherjee, “Political Punishment and Financial Safety Nets: Evidence from India’s Demonetization,” January 2020.

Labonne, Julien, “The Local Electoral Impacts of Conditional Cash Transfers : Evidence from a Field Experiment,” *Journal of Development Economics*, 2013, *104*, 73–88.

Liu, Jiahua and Sheetal Sekhri, “Groundwater Accessibility and Firm Behavior,” Technical Report 2021.

Mahadevan, Meera, “The Price of Power: Costs of Political Corruption in Indian Electricity,” 2021.

Manacorda, Marco, Edward Miguel, and Andrea Vigorito, “Government Transfers and Political Support,” *American Economic Journal: Applied Economics*, 2011, *3* (3), 1–28.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti, “Economic Shocks and Civil Conflict: An Instrumental Variables Approach,” *Journal of Political Economy*, 2004, *112* (4), 725–753.

Nellis, Gareth, Michael Weaver, and Steven C. Rosenzweig, “Do Parties Matter for Ethnic Violence? Evidence From India,” *Quarterly Journal of Political Science*, 2016, *11* (3), 249–277.

Oeindrila, Dube and Juan F. Vargas, “Commodity Price Shocks and Civil Conflict: Evidence from Colombia,” *The Review of Economic Studies*, August 2013, *80* (4 (285)), 1384–1421.

Prakash, Nishith, Marc Rockmore, and Yogesh Uppal, “Do Criminally Accused Politicians Affect Economic Outcomes? Evidence from India,” *Journal of Development Economics*, 2019, *141*, 102370.

Reardon, Sean F. and Joseph P. Robinson, “Regression Discontinuity Designs with Multiple Rating-Score Variables,” *Journal of Research on Educational Effectiveness*, 2012, *5* (1), 83–104.

Sekhri, Sheetal, “Wells, Water, and Welfare: The Impact of Access to Groundwater on Rural Poverty and Conflict,” *American Economic Journal: Applied Economics*, July 2014, *6* (3), 76–102.

____ **and Md Amzad Hossain**, “Water in Scarcity, Women in Peril,” Technical Report 2020.

Shenoy, Ajay and Laura Zimmermann, “Political Organizations and Persistent Policy Distortions,” 2020.

Spellman, Frank R, “Mathematics Manual for Water and Wastewater Treatment Plant Operators,” Technical Report, Boca Raton: CRC Press 2004.

Sukhtankar, Sandip, “Sweetening the Deal? Political Connections and Sugar Mills in India,” *American Economic Journal: Applied Economics*, June 2012, *4* (3), 43–63.

Susewind, Raphael, “Data on Religion and Politics in India,” 2016. Published under an ODbL 1.0 license. Available from https://github.com/raphael-susewind/india-religion-politics.

Tarquinio, Lisa, "The Politics of Drought Relief: Evidence from Southern India," *IED Working Paper No. 354*, 2021.

Thomas Bohlken, Anjali, *Democratization from Above: The Logic of Local Democracy in the Developing World*, New York: Cambridge University Press, 2016.

van der Gun, Jac, "Groundwater and Global Change:Trends, Opportunities and Challenges," *United Nations Educational, Scientific and Cultural Organization*, 2012.

Wade, Robert, "The system of administrative and political corruption: Canal irrigation in South India," *The Journal of Development Studies*, 1982, *18* (3), 287–328.

Wong, Vivian C., Peter M. Steiner, and Thomas D. Cook, "Analyzing Regression-Discontinuity Designs with Multiple Assignment Variables: A Comparative Study of Four Estimation Methods," *Journal of Educational and Behavioral Statistics*, 2013, *38* (2), 107–141.

Wu, Wen-Ying, Min-Hui Lo, Yoshihide Wada, James S. Famiglietti, John T. Reager, Pat J.-F. Yeh, Agnès Ducharne, and Zong-Liang Yang, "Divergent Effects of Climate Change on Future Groundwater Availability in Key Mid-latitude Aquifers," *Nature Communications*, July 2020, *11* (1), 3710.

Zajonc, Tristan, "Essays on Causal Inference for Public Policy," 2012. Harvard University Dissertation, Department of Economics.

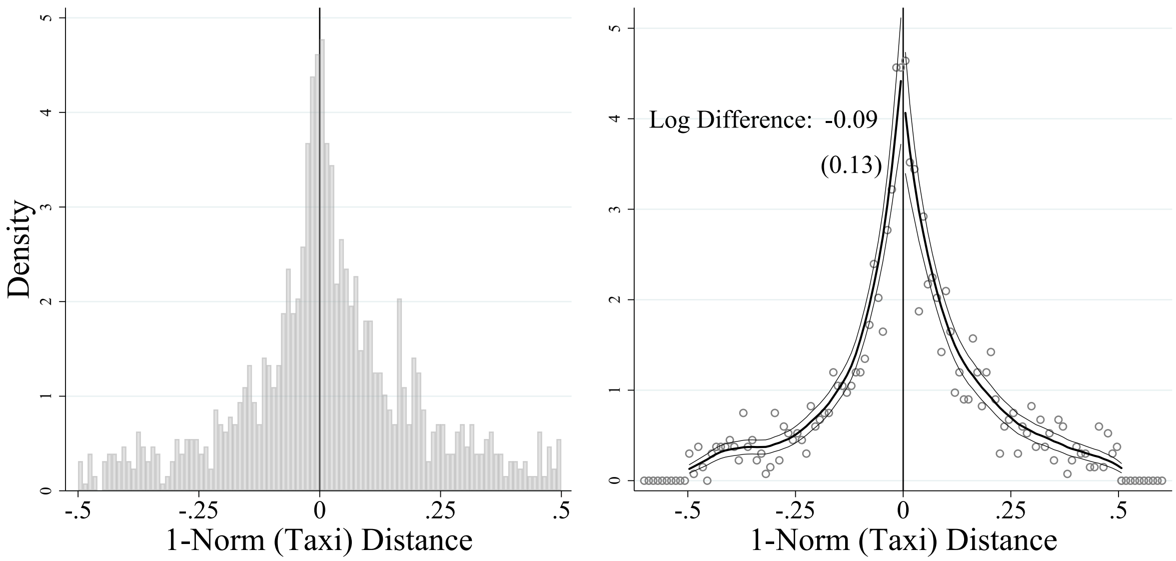
Ziegfeld, Adam, *Why Regional Parties? Clientelism, Elites, and the Indian Party System*, Cambridge University Press, 2017.

Zivin, Joshua Graff and Matthew Neidell, "The Impact of Pollution on Worker Productivity," *American Economic Review*, December 2012, *102* (7), 3652–73.

A Empirical Appendix

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

Figure 4
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	-220.870	-2.039*	0.145	0.095	0.089
	(188.768)	(1.114)	(0.161)	(0.482)	(0.069)
Total Obs	1917	1917	1917	1917	1917
Obs in BW	1238	1223	1277	1287	1341
Bandwidth	0.492	0.471	0.558	0.566	0.698
Robust p-val	0.237	0.108	0.342	0.823	0.168
Mean Left of Cutoff	5007.721	47.963	1.614	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	0.129	-0.112	-1.033	0.616	0.402
	(0.276)	(0.295)	(0.310)	(0.783)	(0.518)	(0.425)
Total Obs	1917	1917	1917	1917	1917	1917
Obs in BW	1341	1206	1216	1330	1331	1345
Bandwidth	0.697	0.444	0.458	0.676	0.677	0.720
Robust p-val	0.233	0.747	0.778	0.207	0.232	0.442
Mean Left of Cutoff	4.377	1.412	2.231	83.026	10.960	6.009

	Percentage of HHs Owning...			
	(1)	(2)	(3)	(4)
	Unirrigated Land	Irrigated Land	Other Land	2013 Avg. NREGA Days
RD Estimate	2.086	0.285	0.003	0.410
	(1.408)	(1.112)	(0.589)	(0.417)
Total Obs	1917	1917	1917	1959
Obs in BW	1202	1180	1226	1267
Bandwidth	0.437	0.410	0.473	0.491
Robust p-val	0.244	0.642	0.925	0.448
Mean Left of Cutoff	20.293	16.218	7.479	5.678

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	0.022	-0.004	0.076	0.104
	(0.016)	(0.021)	(0.208)	(0.210)
Total Obs	11720	11730	16342	16342
Obs in BW	7653	7241	10400	10091
Clusters in BW	1225	1162	1263	1225
Bandwidth	0.489	0.397	0.483	0.429
Robust p-val	0.201	0.756	0.614	0.586
Mean Left of Cutoff	0.431	0.390	6.925	6.200

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

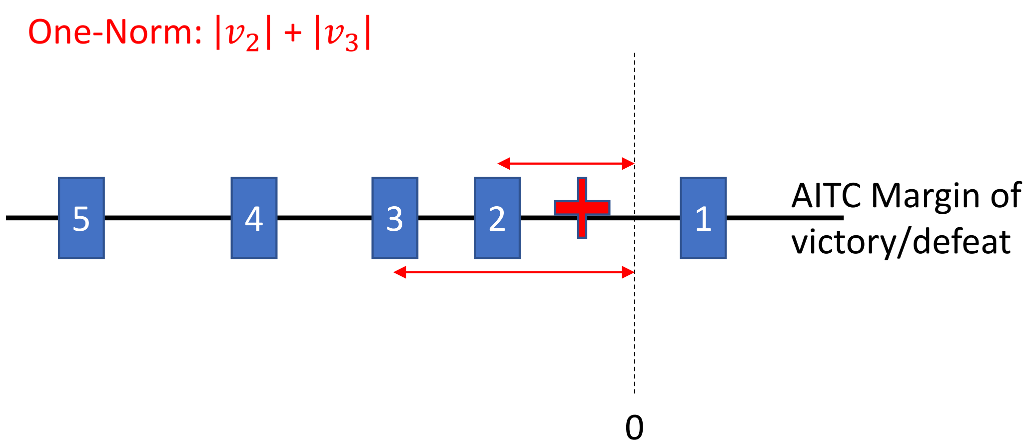
A.3 Defining the Running Variable, Continued

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 5 shows how the one-norm would be calculated for an outcome where the AITC loses four seats in a five-seat council.

Figure 5
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 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	0.856**	0.992***	1.225**	1.600***	0.517	0.478
	(0.347)	(0.288)	(0.550)	(0.476)	(0.466)	(0.388)
Total Obs	7836	7836	3904	3904	3904	3904
Obs in BW	5564	5564	2516	2516	2668	2668
Clusters in BW	1391	1391	629	629	667	667
Control Mean	7.12	7.12	8.17	8.17	6.35	6.35
Bandwidth	0.356	0.356	0.344	0.344	0.233	0.233
Robust p-val	0.025	0.046	0.067	0.040	0.311	0.534
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	0.803*	0.934***	1.298**	1.676***	0.404	0.481
	(0.437)	(0.359)	(0.654)	(0.553)	(0.515)	(0.432)
Total Obs	7836	7836	3904	3904	3904	3904
Obs in BW	4864	4864	2384	2384	2528	2528
Clusters in BW	1216	1216	596	596	632	632
Control Mean	7.33	7.33	8.49	8.49	6.25	6.25
Bandwidth	0.150	0.150	0.180	0.180	0.138	0.138
Robust p-val	0.124	0.123	0.103	0.064	0.534	0.392
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.5 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