Political Organizations and Political Scope

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Abstract

Political checks and balances make different organs of government complementary in the exercise of power. We study how a party organization can seek and abuse these complementarities to expand its influence. We combine data from the Indian state of West Bengal on elections across different levels of government. These are matched to 300 million payments from a welfare scheme that requires approval from both state and local governments. Using a multidimensional close election design, we study the consequences of co-partisan alignment between these two tiers. The state government gives disproportionate funding to co-partisan local officials, who target core supporters to raise votes for co-partisan national candidates. Local officials are rewarded through diverted welfare payments, including a performance bonus immediately after the national election. The ruling party expands its power by recruiting opposition candidates in strategically important local councils, bringing even greater control over public funds.

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1 Introduction

In politics, as in production, there are economies of scope. They arise when control over public funds is dispersed across elected officials at different levels of government. Using or misusing public funds therefore requires coordination between these officials. This is difficult by design. Power is dispersed to prevent any one politician from abusing her office for personal or political gain. But much as firms coordinate supply chains to reduce contracting frictions, a political organization may coordinate veto-holders towards circumventing these checks and balances. If it succeeds it can subvert government resources to finance its own operations in ways unavailable to opponents who control fewer offices. It may exploit its competitive advantage to ultimately deepen and broaden its scope of control.

This paper studies how a political organization can exploit economies of scope to expand its influence, both vertically into new levels of government and horizontally into new political constituencies. The context of our study is West Bengal, an Indian state of 90 million residents. We study how its ruling party exploited state and local control over a massive make-work scheme, the National Rural Employment Guarantee Act (NREGA), to consolidate and grow its power. While the state government ultimately controls which local governments receive NREGA projects, the local councils control the allocation of NREGA jobs to villagers within their jurisdiction (called the gram panchayat, or panchayat for short). This dispersion of power creates complementarities between control of the state and local governments. The ruling party, which first took control of the state government in 2011, subsequently won absolute majorities on many local councils in 2013. We exploit quasi-random variation created by close contests in this local election to study the impact of complementary control. We show how the party used the program to expand "vertically" during the subsequent national elections in 2014, and "horizontally" in the following years by recruiting opposition councilors in local governments where it originally failed to win a majority.

Our research design is based on a local institutional setup that is common worldwide, although a quirk relative to other Indian states. Local candidates in West Bengal campaign with explicit party affiliations to represent a single constituency in a local council. These elected councilors then choose a president who, with the consent of the majority, administers antipoverty programs—essentially a Westminster model. Whichever party holds an absolute majority can appoint a president who is unconstrained by coalition partners, giving the party sole discretion over which individuals get NREGA payments. The majority party is determined by the collective outcomes of the individual council member races. The margins by which these seats are won or lost determine how close the state's ruling party came to winning or losing the absolute majority. Using a multi-dimensional regression discontinuity design, we construct the univariate distance to the threshold of having an absolute majority. We causally identify how the ruling party shifts resources when it narrowly takes control of the council in closely contested elections. Crucially, we can distinguish how the party acts when it holds an absolute majority, and thus complete control, from the case where it is merely the largest party and holds the presidency subject to the veto of a coalition.

We measure its actions by scraping and compiling administrative records for 300 million NREGA payments made to named individuals spread across an eligible pool of 11 million households. We combine these records with data on thousands of candidates contesting the 2013 local council elections, and polling station-level data on vote returns for the 2014 national election. We leverage this unique dataset to study program allocations across and within gram panchayats. We can observe whether it targets politically loyal constituencies, and whether it siphons funds to its own candidates and the opposition candidates it recruits. These data, together with our design, is what makes it possible to identify whether the mechanism driving our results is complementary political control.

We find that panchayat councils barely controlled by the state ruling party receive 12 percent higher aggregate program allocations than areas where it barely misses the absolute majority. During the 2014 national election, panchayats narrowly controlled by the ruling party return an additional 2 percentage points for its parliamentary candidate. We rule out that the over-allocation of funds is driven by co-partisan efficiencies, or that the voting effects are driven by the endorsement of the local president, by exploiting the difference between holding an absolute majority versus being the largest party. We construct a different running variable that measures how close the ruling party came to being the largest party in the local council. We show that the AITC is far more likely to hold the presidency when it becomes the largest party even when it does not hold an absolute majority. But we find no similar surge in NREGA funds, suggesting the state government will not allocate excess funds to local councils where a coalition creates additional checks and balances. These areas also show no increased electoral returns, suggesting it is the funds and not a presidential endorsement that drives the electoral returns.

But is the mechanism for this effect necessarily direct action by local officials on behalf of the national candidate? And if so, how does the party organization sustain their cooperation? We answer the first question by testing for evidence of politically-motivated targeting of the program in the lead-up to the national election. We show that *within panchayats* controlled by the ruling party, the areas with higher ruling party vote share in prior elections—and thus more ruling party voters—receive consistently higher payouts both in and after the national election. This result holds regardless of whether there is an elected ruling party councilor in the area. Since all areas within the panchayat are governed by the same council, this result is hard to rationalize except as a reward for supporters of the ruling party. Meanwhile, we find that demographics correlated with poverty are no more likely to get jobs when the ruling party takes control.

These results suggest that local officials are distorting payments to muster support for national co-partisans. This result is more surprising than it seems because the national candidate has no direct means of rewarding local officials. How does the party organization buy their cooperation? We answer this question by studying payments made through the jobs scheme to the local politicians themselves. We find that panchayat councils controlled by the ruling party make excess payments to job cards registered to its local candidates. These payments are more than twice as large as the already magnified payments to typical households in these panchayats. Party candidates receive the same excess payments *regardless whether they won or lost their own races*. Since losing candidates hold no official position, they could not have authorized these payments personally. Instead, they could only have been made with the complicity of the party. That suggests the corruption is a feature of the party organization rather than an individual abuse of power.

In addition to fixed payments, we also find suggestive evidence of incentive pay. In panchayats controlled by the ruling party its candidates receive a bonus payment in the 4 weeks immediately after polls close in the national election. This payment is systematically larger for candidates from areas that returned more votes for the ruling party. This effect cannot be explained by the results of earlier elections or the overall size of payments received by non-candidate households. And there is no similar pattern in a non-election year, suggesting the payment is directly linked to the election. It is consistent with a scheme that rewards local candidates for turning out voters for the national candidate. Taken together these results suggest it is the opportunity for self-dealing that aligns incentives and undermines checks and balances.

Aside from expanding its vertical scope into new levels of government, a party organization can expand its horizontal scope to take control of new areas. We test for whether and how the party takes control of additional local councils by inducing officials aligned with the opposition to switch allegiance. We measure party-switching using the party affiliations of candidates in the subsequent 2018 local election. We infer that an individual registered under a different party in 2018 than in 2013 has switched parties. We show that the ruling party is far more likely to retain candidates than the opposition, and opposition candidates who switch to a new party are overwhelmingly switching to the ruling party. We find that the ruling party candidates who switch also typically receive less money through NREGA, whereas opposition candidates who switch—especially those who switch to the ruling party—are paid more. Among candidates from the two main opposition parties, this effect only occurs for those who won their election in 2013 and thus can help the ruling party gain majorities on councils where it did not win enough seats in 2013 to control the council. The ruling party on average sees no net recruitment in panchayats where it already holds a majority. In short, the party gains recruits only in places where it needs them, suggesting the effect is not merely a unilateral decision by opposition candidates to join the winning side.

The net impact is to further consolidate the power of the ruling party. Although the 2014 national election came too soon for the consequences of this effort to be visible, by the 2016 state election these panchayats are returning votes for the ruling party at the same rate as panchayats where it did win the majority. The effort is so effective that the discontinuity in vote returns visible in 2014 has vanished by 2016, and it is largely because of improved returns in "control" panchayats.

Taken together our results imply that the party organization plays a key coordinating role in the pursuit and abuse of power. We show that *state officials* channel funds to *local officials* to assist with the elections of *national politicians*. It is hard to imagine such trilateral coordination could arise from decentralized clientelism or a standard model of incumbency-driven targeted spending. These models would likewise fail to account for the organization's role in exploiting the complementarities created by fiscal checks and balances. The arrangement is *unavailable to other parties* even if they do hold absolute majorities on the local council because the state ruling party can effectively starve them of projects.

Demonstrating the role of political complementarities is our key contribution. It has the biggest implications for the empirical literature on politically targeted spending.[1] Much of this work has focused on the incentives of incumbent candidates and parties to win their own election by targeting government resources to either swing or core constituencies (Bardhan and Mookherjee, 2006; Golden and Picci, 2008; Cole, 2009; Baskaran et al., 2015). Though the actors in these studies are often parties, the importance of the party organization itself is not central to their hypothesis. The predictions would be similar for a single elected official contesting her own election, and thus the targeting is based on the political lean of a constituency rather than the allegiances of local officials. The exceptions are a few studies (e.g. Brollo and Nannicini, 2012; Curto-Grau et al., 2018) that study whether state or national resources are targeted to co-aligned local officials. The specific resources are generally infrastructure or earmarked funds that are discretionary at the higher level but not locally, making the mechanism entirely different from the one we study. The mechanism proposed in these prior studies is that higher level officials help local officials with their own election, who may return the favor in future elections (as in Persico et al., 2011).[2]

Our results cannot be driven by this mechanism because both state and local officials are working on behalf of a national candidate. Our work is unique in studying resources that are jointly controlled by two levels of government, making complementary control the key mechanism. Our work is also unique in having an institutional context and a massive individual-level dataset that lets us explore multiple aspects of the mechanism, from multi-level targeting to incentive-based payments. The mechanism we propose is potentially more pernicious than those of earlier models because it is inherently dynamic. An incumbent seeking reelection can at worst tilt the odds to keep herself in power. An organization that gains control of a comple-

[1] For an overview of the literature on distributive politics see Golden and Min (2013).

[2] Asher and Novosad (2017) show evidence of a different kind of favoritism where ruling party state legislators are able to influence bureaucrats to fast-track permits and cut red tape. This is a substantially different mechanism from any of these other papers (and our own).

mentary office can unlock additional government resources it can use to not only hold power but to expand its power.

Our work is also related to the theoretical literature on political parties. Most prior work has modeled parties as either bundles of policies (Downs, 1957; Aldrich, 1995; Levy, 2004; Anesi et al., 2009) or vehicles that arise to mobilize and advocate for segments of voters united by attributes, ideology or economic interests (Lipset and Rokkan, 1967; Stokes, 2003; Chandra and Boulet, 2012; Muirhead and Rosenblum, 2020). Our approach instead draws on organizational economics, which posits that firms exist to resolve contracting problems that arise when there are complementarities in production (Coase, 1937; Gibbons and Roberts, 2012). To our knowledge this is the first paper to apply the framework to understand how party organizations exploit complementarities that arise from holding different political offices.

Finally, our work also draws on the literature on clientelism. Most of this literature focuses on the bilateral relationship between a patron and his supporters (see Hicken, 2011, for a review). A traditional model of clientelism envisions little role for an organization. A relatively new subset of the literature studies how several puzzling strategies followed by patrons can be explained by their need to hire intermediary "brokers," which comes closer to our work by expanding the set of agents (Stokes et al., 2013). Our micro-level targeting results could be consistent with clientelism and brokers, but the precise mechanism of the targeting is not the focus of our study. We focus on the role of the organization in circumventing checks and balances that would otherwise prevent accessing government resources to finance clientelism (or any form of targeted spending). The coordination between state and local officials on behalf of a national candidate provides clear evidence that a political organization can be more than an association of patrons using similar methods of brokerage and patronage.

2 Model

2.1 Setup

There is a state politician who controls the aggregate benefits ("projects") allocated to each locale k. She allocates projects to maximize both social welfare and the vote return from targeting funds:

$$\max_{\{B_k\}} \left[\sum_k W_k(B_k) + \alpha \sum_k V_k(B_k) \right] \tag{1}$$

subject to

$$\sum_k B_k = \bar{B} \tag{2}$$

The term $W_k(B_k)$ is the (indirect) welfare function for the allocation of projects to locale k, and $V_k(B_k)$ the vote return. The parameter $\alpha \geq 0$ captures the relative importance of generating votes in the election. Note that $V_k(B_k)$ is *not necessarily votes in the state politician's own election*, merely votes for a particular candidate in some election. It is possible that $\alpha = 0$ implying the state politician does not care about this election.

Locale k is governed by a local politician who decides which individuals receive benefits ("jobs") from the aggregate allocation B_k. He allocates benefits to maximize both the welfare of households under his jurisdiction and an electoral objective that may or may not coincide with that of the state politician:

$$\max_{\{b_i\}} \left[\sum_i u_i(b_i) + \beta_k \sum_i v_i(b_i) \right] \tag{3}$$

subject to

$$\sum_i b_i = B_k \tag{4}$$

The term $u_i(b_i)$ gives the indirect utility to household i from receiving b_i jobs. The term $v_i(b_i)$ gives the expected vote return from targeting i. The term β_k, as we shall explain, captures the extent that the electoral objectives of the two politicians coincide.

Let $\{b_i^*(B_k;\beta_k)\}$ be the set of benefits that maximizes (3) subject to (4). Impose the following conditions to relate Equation 1 to Equation 3:

$$W_k(B_k) = \sum_i u_i\left(b_i^*(B_k;\beta_k)\right) \tag{5}$$

$$V_k(B_k) = \sum_i v_i\left(b_i^*(B_k;\beta_k)\right) \tag{6}$$

These conditions imply that the state politician's payoff from giving additional projects to k depend on how the local politician allocates benefits. The key question is whether α and β_k have the same sign, which implies the political objectives of the politicians are aligned.

2.2 Distinguishing Political Complementarities from Existing Models

This general model nests several of the most common models in the literature.

Targeted Spending/Pork-Barrel Politics: Assume $\beta_k = 0$, meaning the local politician simply allocates benefits to maximize local welfare, and that $v_i(b_i) = \lambda_k u_i(b_i)$ for some constant λ_k that captures the electoral significance of k in the election. Under this assumption the electoral benefit depends solely on total benefits to the locale. If this is the state politician's own re-election, meaning α is large and positive, then the state politician allocates disproportionate projects to locales where λ_k is relatively high. If this is not the state politician's own re-election, meaning $\alpha = 0$, then there is no political misallocation. Crucially, the misallocation does not depend on who runs the local government. The model of Political Fiscal Cycles is a special case where $\alpha > 0$ in an election year and $\alpha = 0$ in a non-election year.

Decentralized Clientelism, Vote- or Turnout-Buying: Assume B_k is fixed (say, by law) and only the local politician's decision matters. In the standard model of clientelism β_k is large and positive. The local politician allocates benefits to individual voters in return for their allegiance, which includes voting for the politician during the election. The model of vote-buying is similar except that β_k is large and positive only during an election year, and zero otherwise.

Partisan Favoritism: Define an indicator ω_k that equals 1 if the top-ranking official in k is a member of the state politician's party (or faction, or ethnicity). One version of this theory assumes pure in-group preference, which can be represented by modifying Equation 5 to $W_k(B_k) = \omega_k \sum_i u_i\left(b_i^*(B_k; \beta_k)\right)$. Another version assumes the state politician wants to elevate the standing of her factional allies (Persico et al., 2011), which can be represented by modfying Equation 6 to $V_k(B_k) = \omega_k \beta_k \sum_i v_i\left(b_i^*(B_k; \beta_k)\right)$. In both cases it is assumed that 1) $\alpha = \beta_k = 0$ if neither state nor local politician is up for election and 2) ω_k is defined based on the identity of the top-ranking official rather than on control of local resources. These are two of the crucial distinctions between partisan favoritism and complementary control, and are among the tests we describe in the next two sections.

2.3 Complementary Control

Misaligned Incentives—Ambition Checks Ambition: Political complementarities arise in this model because the state and local politician act as checks on one another. To see why, consider the Madisonian ideal where $\beta_k = 0$ whenever $\alpha > 0$, and vice-versa. If $\beta_k = 0$ then the targeting of benefits $\{b_i^*(B_k; \beta_k)\}$ chosen by the local politician will maximize local welfare W_k. To the extent that v_i differs from u_i, the political impact will be blunted because $b_i^*(B_k; 0)$ will not be targeted to maximize V_k. Knowing that *jobs* will not be targeted to maximize political returns, the state politician has less incentive to allocate *projects* for political gain (see Appendix A.1.1).

Conversely if $\beta_k > 0$ and $\alpha = 0$, the state politician will allocate projects to maximize welfare *conditional on the local politician's targeting*. To the extent that the local politician mis-targets benefits for political reasons, it will decrease the aggregate welfare of households in the locale $W_k(B_k)$. The state politician will respond by allocating fewer benefits. Her response effectively disciplines the local politician. If he mis-targets too egregiously his budget will be cut (see Appendix A.1.2).

Aligned Incentives—The Role of the Organization: The party organization exists to align the incentives of these politicians. It first ensures that $\alpha > 0$ in any election contested by a member of the organization—in particular, a national election contested by members of the ruling party. Suppose the national politician can promise to deliver federal transfers to the state politician (by increasing the size of $\bar{B}$). The role of the organization is to enforce this unofficial contract (say, by threatening to expel the national politician if he reneges). Given this credible promise, the state politician is willing to over-allocate projects to locales important to the national politician's election.

Given that $\alpha > 0$, the organization will likewise ensure that $\beta_k > 0$ in any local government controlled by members of its organization. To be precise, there are three cases:

- Ruling party organization has complete control of local government: $\beta_k = \alpha > 0$
- Opposition party organization has complete control of local government: $\beta_k = -\alpha < 0$
- Ruling party organization governs local government in coalition: $\beta_k = 0$

In Case 1, objectives are fully aligned and the ruling party can exploit complementary control. Jobs that come with any project allocated to k will be targeted to generate electoral returns as well as household welfare. In Case 2, objectives are opposed. Jobs that come with any project will be targeted to *reduce* electoral returns for the ruling party candidate. In Case 3, the checks and balances hold because the coalition can bring down the ruling party if it engages in political targeting.

The model then makes several predictions:

Prediction 1 (Complementary Control) *1. The state politician allocates more projects (aggregate jobs) to local governments controlled by the ruling party*

2. The ruling party's national candidate reaps more votes in locales controlled by the ruling party

3. These effects are either absent or muted in areas where the ruling party governs but does not have complete control

It is crucial to note what makes these predictions distinct from the usual models of pork-barrel politics or co-partisan favoritism. Misallocating funds to co-partisan governments is not the same as geographically targeting funds. The prediction is not driven by the electoral significance of the locale but by control of the local council. Co-partisan favoritism, on the other hand, predicts more projects will be allocated to a locale where the leader is a member of the ruling party, *regardless of whether there is an outside check on his control.* Finally, neither model predicts that state or local politicians will distort allocations for the sake of a third national politician who has no direct authority over either.

2.4 Mechanisms: Targeting and Financial Incentives

The key mechanism behind Prediction 1 is that locales controlled by the party get extra projects *with the expectation that the local politician targets politically valuable households.* This mechanism is another key distinction from standard models of pork-barrel politics and co-partisan favoritism. To illustrate this mechanism, impose the following assumption:

$$v_i(b_i) = \lambda_k \gamma_i u_i(b_i) \tag{7}$$

The difference between this assumption and the one imposed for simple pork-barrel politics (in Section 2.2) is the term γ_i, which captures the electoral significance of the *household* as distinct from the locale. This assumption implies there are specific households *within the locale* who are more likely to vote for the ruling party if they receive a job (those with high values of γ_i). It yields the following prediction:

Prediction 2 (Within-Locale Targeting) *Within a locale controlled by the ruling party, benefits will be targeted to politically significant households or areas.*

Our model does not make a specific prediction about whether households with high values of γ_i are core supporters, as would be true for a model of brokers or turnout-buying, or swing voters, as in a model of vote-buying. It also does not require or rule out conditionality, as in a model of clientelism. It only predicts some within-locale targeting based on political preferences. Hence our model is not mutually exclusive with any theory of micro-level targeting. It embeds them within a larger system to explain how aggregate targeting arises from the anticipation of subsequent micro-targeting.

The other key mechanism in our model is that the organization actively motivates the local politician to engage in targeting. Section 2.3 simply imposed that $\beta_k = \alpha > 0$, which would hold if the organization punishes the local politician for not targeting benefits correctly. But this is only possible if the organization observes $\{\gamma_i\}$, which may not hold if the local politician has private information about the electoral significance of each household. Then the accuracy of the local politician's targeting is essentially a hidden action. The theory of organizational economics predicts that a firm can alleviate moral hazard by offering incentive pay: a wage that is a function of the outcome of the worker's effort. If the local politician is allowed to divert funds to himself—that is, engage in self-dealing—the organization can use diverted funds to sustain cooperation.

Amend Equation 3 to

$$\max_{\{b_i\}} \left[\sum_i u_i(b_i) + u_L(w_k) \right] \tag{8}$$

where $u_L(w_k)$ is the local politician's utility from diverted funds w_k. If $u_L' > 0, u_L'' < 0$ then the optimal contract will include both a constant payment—a wage—and a payment increasing in the electoral return V_k—a performance bonus (Hölmstrom, 1979).

Prediction 3 (Compensation) *The local politician will receive fixed and incentive payments through diverted funds.*

There is one small but crucial nuance in taking this prediction to the data. The formal authority to target benefits lies with the local council (as long as the ruling party holds a majority). But individual local council candidates, by virtue of their presence in a district, are likely the ones who observe and report $\{\gamma_i\}$, and the ones who make any complementary electioneering (e.g. telling voters that they got the job solely through the party's intercession). Since the individual candidates face the moral hazard problem, we would expect them to receive the fixed payments, and the incentive payments based on returns from their own area within the locale.[3]

2.5 Long-Run: Horizontal Expansion

Section 2.3 predicts the party organization will align state and local incentives to assist a national politician: vertical expansion. But it also has an incentive to expand horizontally to take control of more locales. It has this power because the state politician can both starve opposition-controlled locales of funds and offer payments to local politicians who switch.

To be precise, suppose that each local government contains several local councilors. A party organization (either that of the ruling party or the opposition) gains control of the local council if it has a majority. A councilor will want to switch parties if Equation 8 is made higher if they switch than it would be otherwise. The ruling party (opposition) will accept the new recruit if Equation 1 is made strictly higher (lower) by the switch. Since the ruling party controls the allocation of projects, all local councilors will want to either remain with or switch to the ruling party. But the ruling party will only accept new recruits in areas where it does not already control the local government.

Prediction 4 (Recruitment) *The party recruits local councilors in locales that it currently does not control ($\beta_k \leq 0$). It will not recruit in locales it already controls ($\beta_k > 0$).*

3 Context

[3] This prediction holds regardless of whether the candidate holds a seat on the council, which distinguishes it from the prediction of the next section.

3.1 The State Ruling Party and Elections in West Bengal

The Indian state of West Bengal is in eastern India and in 2011 had a population of about 90 million. India is a federation that holds national, state, and local elections. At all levels one full term lasts 5 years, but elections take place on different cycles. During our analysis period from 2013 to 2018, the All India Trinamool Congress (AITC) was in power at the state level in West Bengal. The political party is headed by its founder Mamata Banerjee, who has been the chief minister (the head of the state government) since the 2011 assembly elections when the AITC defeated the incumbent Left Front government that had held power for 34 years. This provided the AITC with access to state financial resources for the first time. In the subsequent local elections of 2013 the AITC won an absolute majority in about 55 percent of panchayats, giving it control over two levels of government in much of the state.

With these electoral successes under her belt, Mamata Banerjee and the AITC were widely expected to play the key kingmaker role in the 2014 national elections. The election was expected to yield a hung parliament. Since the AITC was projected to win most of the seats in West Bengal this would give the AITC substantial bargaining power to decide on the next prime minister.[4] She made repeated statements that regional parties should join forces to create a Federal Front to provide a third alternative to the two big national parties. Coming on the heels of her election campaign kickoff speech 'Dilli chalo' (Let's go to Delhi), these statements were widely interpreted as indications of her ambitions to play a key role in national politics and to potentially even become the Prime Minister herself (Mitra, 2014; Paul, 2018). The AITC won 34 of West Bengal's 42 seats in India's Lower House in the 2014 election, a massive gain relative to the 18 seats won in the previous election. To Mamata's big disappointment, she was sidelined due to the landslide victory of the Hindu nationalist BJP outside of West Bengal.[5]

The AITC's success has little to do with vision, ideology, or appeals to caste. It is primarily a strategic vehicle for political power sustained by centralized coordination.[6] Mamata Baner-

[4] "Predictions are that the next Lok Sabha will be another hung one… And with twenty-nine MPs, Mamata's bargaining power will not only shoot up, she may even call the shots." (Mitra, 2014)

[5] The Economic Times, 'Election Results 2014: Despite Winning in West Bengal, Mamata Banerjee Maintains Belligerence, May 17, 2014.

[6] Mitra (2014), who has followed Mamata Banerjee as a journalist, writes: 'However, there is little question that most of [AITC] is made up of political lightweights with little or no vision of their own or, as pointed out above, with little depth of ideological commitment to Mamata's vision of a Bengal renaissance.'

jee takes a strong interest in decisions about which politicians receive party tickets and is well known to keep a close eye on activities of party members at all levels of the party hierarchy. Multiple elected state politicians have reported that they were unable to make even small changes in their constituencies, such as installing a few urgently needed handpumps, without the knowledge and permission of the party leader (Mitra, 2014).

The consequence of this meticulous coordination is that the party has systematically expanded its power. As early as 2014, the journalist Mitra (2014) wrote:

> For the foreseeable future, there seems to be no escaping the slippery slope to quasi-autocracy in West Bengal. . . it is not voter intimidation or any other coercive power-maintenance strategy we normally associate with autocracies. Instead, Mamata's regime will maintain power because it will continue winning election after election, just as the Left had done.

3.2 Local Government Structure in West Bengal

The lowest elected tier of politicians are those elected to the panchayat council. The panchayat council makes policy decisions that apply within its jurisdiction. Somewhat confusingly, this jurisdiction can contain multiple villages, which is especially common in large states like West Bengal. This is an important feature for our empirical analysis, since we have data on the allocation of welfare benefits both between the jurisdictions of different panchayat councils, as well as between different villages within the jurisdiction of the *same* panchayat council. We refer to the jurisdiction of a council as *panchayat* to distinguish it from the villages it contains.

In panchayat council elections, the panchayat area is divided into wards. Voters in West Bengal then elect the political candidate in the ward they live in. The council therefore consists of one elected member from each ward.[7] The president of the council is not elected directly by voters, but is chosen indirectly in a vote by the council members. Partly because of this Westminster-style arrangement, political candidates in West Bengal campaign with explicit party affiliations (since no one candidate or election will set the direction of the government). While this makes the institutional setup somewhat unusual for local governments within India, it is a common setup in many other countries and is a direct parallel to India's state and national government.

[7] The number of wards depends on the population size.

As in other states the council president makes executive decisions, including decisions about which individuals receive NREGA benefits (see next section). But she serves at the pleasure of the majority, which has the formal authority to remove her from office through a resolution by the majority of the councilors.[8] A political party that controls the majority of seats in the gram panchayat is therefore insulated from the opposition in a way in which presidents in areas where their own party falls short of the absolute majority are not.

Mamata Banerjee has systematically reduced the independence of local politicians in panchayats controlled by the AITC:

> "'Earlier, in the CPI(M) regime, the local party leader at the grassroots level was very important. He would decide everything . . . Mamata has reduced the role of the local politician. Today, it is all . . . controlled by her.' (Paul, 2018)

3.3 The Welfare Program NREGA

One of the largest responsibilities of the local government is to implement the welfare programs of the central and state governments in their area. The biggest anti-poverty program with some of the most sought after benefits is the National Rural Employment Guarantee Scheme, typically referred to as NREGA based on the accompanying Act. According to Dey and Sen (2016), NREGA accounts for 80 to 90 percent of local total annual expenditures, even though panchayat councils in West Bengal implement about 25 anti-poverty programs.

On paper, NREGA guarantees every rural household up to 100 days of employment on public-works projects. Households can request work whenever needed throughout the year and are paid the minimum wage. There are no further means tests (Dey et al., 2006; Government of India, 2018; Zimmermann, 2021). The central government intended NREGA to be a flexible safety net for rural households dealing with underemployment, seasonality and unexpected income shocks. In practice, the actual employment provided to households falls substantially short of the demand from households in most states, including in West Bengal. This leads to rationing, and many households report having to wait passively for work to become available (Dutta et al., 2012; Mukhopadhyay et al., 2015).[9]

[8] See Section 12, West Bengal Panchayati Raj Act

[9] Nevertheless, previous research has shown that despite the shortcomings NREGA helps households better deal

This setup gives politicians extensive power in deciding how NREGA employment is allocated between and within panchayats. While the national government pays for most of the scheme, state governments make important decisions on how to allocate NREGA funds within the state. Within a panchayat, the panchayat council and especially the panchayat council president determine how NREGA is implemented. They register households, propose local projects to sub-district and district officials, and assign individuals to work projects. A worker who wants NREGA labor must apply at the council office. These allocations are then submitted to higher-level officials, who approve the wage payments. To increase transparency about NREGA allocations, panchayat councils are required to keep physical records of muster rolls and to enter all NREGA-related information into a software application called NREGASoft (Government of India, 2013). The administrative data from the application is published in close to real time on a publicly available website dedicated to NREGA.[10][11] We use information scraped from this website for our analysis.

Is the data credible enough to study the potential misallocation of NREGA resources? By 2013, any payment for NREGA labor would only be approved if registered in the online system. We can thus reasonably assume that any diversion of funds or self-dealing recorded on the website captures an actual payment made to the bank account or post office account of the named beneficiary. Though it is possible that NREGA funds may be diverted through other aspects of the program (notably through payments for materials), any payment for labor during our sample period must go through the online system. By law, expenditures on labor must account for the majority of total expenditures, ensuring that we observe the bulk of any corruption or diversion of resources. That said, it is possible that what we observe is an underestimate of favoritism in the allocation of benefits. By contrast, it is unlikely that we overestimate it, as the ruling party is unlikely to publish self-dealing in the online system while hiding legitimate payments in the

with shocks, and NREGA employment is typically much higher during periods such as the agricultural off-season when households in rural areas have few alternative job opportunities. See e.g. Imbert and Papp (2015) and Zimmermann (2021).

10 https://nrega.nic.in

11 To cut down on corruption, NREGA profiles are linked to biometric markers through a national identification ('Aadhar') number, and the central government directly transfers wages for completed work into beneficiaries' bank accounts. Muralidharan et al. (2016) find that these features have substantially improved targeting and overall household benefits, plausibly by making it much more difficult to impersonate beneficiaries or intercept the benefits.

less transparent parts of the system.

Expenditures on social welfare schemes increased once Mamata Banerjee came to power at the state level (Paul, 2018). Based on interviews and her own observations, Mitra (2014) describes Mamata Banerjee's approach to social welfare programs as piecemeal and extremely pragmatic, with little interest in truly using programs like NREGA to reduce poverty. Mamata Banerjee has claimed credit for her implementation of NREGA as one of her achievements, and while actual work is done at NREGA worksites, this is used to maximize the employment opportunities and not the usefulness of projects for local development.[12] Paul (2018) believes that rural welfare schemes are a key explanation for the AITC's continued success despite multiple high-profile corruption scandals.

4 Research Design

4.1 Data

We scrape roughly 11 million West Bengali NREGA job card profiles from the official government portal (http://nrega.nic.in). Each profile contains the name of the household head and all household members registered under the job card, as well as the election photo ID card number of the registrant; panchayat and village of the job card holder; and the project name, start date, days of labor, and total payment for each job spell. The full sample amounts to roughly 300 million job spells.

We merge these job cards to data on the outcome of each local council ward race from the 2013 local elections. These data are scraped from the website of the State Election Commission of West Bengal. Each record gives the party, ward, and vote returns of each candidate (as well as the candidate's name, caste group, and gender). We supplement these data with information collected from district offices on the names of panchayat council officers, which let us identify which elected panchayat council member is the council president.

We digitize PDFs of polling station-level returns from the 2014 national election downloaded

[12] Mitra (2014) quotes an AITC activist saying "…hundreds of people are being employed to do a job that perhaps requires about half the number…you will find countless men and women at the work site shovelling soil and carrying it from one spot to another. The next day you will find them shovelling it up from that spot and carrying it back to the original spot.'

from the Chief Election Office of West Bengal. The station identifiers are merged to station names and geocoordinates using data from Susewind (2016). We identify the polling stations within each panchayat by querying election photo ID cards from the NREGA data against the Chief Election Office's website, which we use to construct a station-to-panchayat crosswalk.

Finally, we merge data from the 2011 Census to the panchayat-level election and NREGA data. We build a crosswalk between Census villages and panchayats using data scraped from West Bengal's Panchayat Raj Department. We then aggregate the village-level census data by panchayat. We describe the precise steps for merging and aggregation, as well as the sources of the underlying data, in greater detail in Appendix C.

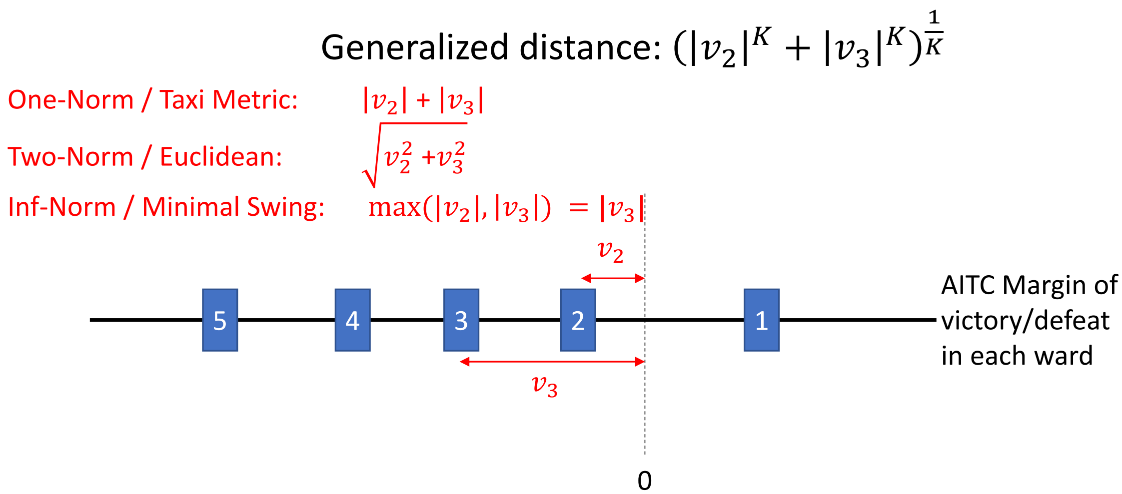
4.2 Defining the Running Variable

Unlike most Indian states, West Bengal uses a Westminster system to govern its panchayats. The panchayat is divided into wards that each elect a council member, and the council then chooses a president. This system is a strength of our context because it lets us distinguish the impact of holding an absolute majority from that of leading a coalition as the largest party. But it also raises a challenge because there is no single vote count that determines control of the council. Since we cannot use a simple univariate regression discontinuity design, we instead define a multidimensional running variable (Feigenbaum et al., 2017).

This approach is most easily understood through a simple example. Suppose a panchayat has 5 wards, where the AITC candidate wins in Ward 1 by a margin of 10 percent while losing in Wards 2, 3, 4, and 5 by margins of 5, 10, 15, and 20. Figure 1 illustrates this scenario. The "closest" counterfactual outcome where the AITC would have won an absolute majority is one where, holding the results in all other wards unchanged, it barely won in Wards 2 and 3. Since it lost those wards by 5 and 10 percent, one measure of the distance would be $|5| + |10| = 15$, which is the 1-norm. Since the AITC lost, the actual value of the running variable would be -15 (putting it to the left of the cutoff). An alternative distance measure would be $-\sqrt{|5|^2 + |10|^2} \approx -11.18$, the Euclidean or 2-norm. There is a continuum of alternative measures $(|5|^k + |10|^K)^{1/K}$ for each choice of K, but all shrink to zero as the outcome "approaches" an AITC absolute majority.

More generally, in any panchayat of N wards where the AITC did not win an absolute ma-

Figure 1
An Example of Calculating Distance Metrics



Note: The 1-norm, 2-norm, and infinity-norm in a case where the ruling party (the AITC) wins 1 seat and loses 4. Counterfactually the AITC would have had to have won seats 2 and 3 to win the majority. Each measure of "distance" to the cutoff of an AITC majority plugs the losing margins of those two seats into the expression for the norm.

jority, we identify the M additional seats the AITC would have needed to have won to gain an absolute majority. Let $v_1, v_2, \ldots, v_M$ be the vote margins of the AITC candidate in the M seats where it came closest to winning. Define the K-norm as

$$D_k = \left[\sum_{m=1}^{M} |v_m|^K \right]^{1/K}$$

Our main specification sets $K = 1$, but we also show results for $K = 2$ and $K = \infty$ (all of which are depicted in Figure 1). The running variable would be signed as negative, since negative values imply that the AITC does not control the panchayat. We follow an analogous procedure for panchayats where the AITC did win an absolute majority, except we identify the M seats it would have had to have lost to not have the absolute majority.[13] These outcomes where the AITC won an absolute majority are signed to be positive.

Our preferred metric throughout the paper is the 1-norm, which can be interpreted as the total number of percentage points of votes the AITC would need to 'buy' across all wards to get control of the panchayat council. This metric is more intuitive than the Euclidean norm and less

[13] If the panchayat council has an even number of seats we define an absolute majority as 50% + 1 seats.

noisy than the infinity norm, although our results are not sensitive to the choice of norm. We estimate changes at the cutoff with several specifications.

4.2.1 Tests for Manipulation of the Running Variable

In Appendix B.1 we report several tests for manipulation of the running variable. We first test for whether there is a discontinuity in the density of the one-norm at the margin where the AITC wins an absolute majority. Any such discontinuity would imply that the AITC or one of its competitors is able to manipulate the outcomes of elections to ensure it wins barely enough votes in barely enough seats to win a majority. Manipulation of the vote count is implausible because the Election Commission of India is a non-partisan bureau that is widely respected and considered free from corruption. Applying the test of McCrary (2008) shows no evidence of any discontinuity. Appendix B.1 also tests for discontinuities in panchayat-level outcomes measured in the 2011 Census. Since the census was taken before the 2013 election, a discontinuity would suggest there was manipulation. We find no evidence of discontinuities in population, caste composition, or the presence of various public goods. We also find no discontinuities in political outcomes in prior elections, or pre-election NREGA allocations.

4.3 Specifications

4.3.1 Basic RD

Our main specification estimates the discontinuity in outcomes using a local linear regression of the form

$$Y_{kt} = \phi_0 + \phi_1 d_k + \phi_2 d_k M_k + \beta M_k + X_k \boldsymbol{\gamma} + \varepsilon_{kt} \qquad \text{for } k \text{ such that } |d_k| < h \tag{9}$$

where Y_{kt} is the outcome for a panchayat k in year t, d_k is the running variable (the 1-norm in most specifications), and M_k a dummy for whether the AITC holds the absolute majority on the panchayat council. The coefficient β gives the regression discontinuity estimate. We estimate the bandwidth h using the optimal bandwidth proposed by Calonico et al. (2014). We weight observations using a triangular kernel. For specifications that pool observations across years we cluster standard errors by panchayat. In those where we have only a single observation per panchayat (e.g. vote share in the 2014 election) we use the 3-nearest-neighbor estimator for standard errors (which is more conservative than the usual heteroskedasticity-robust standard error). In some specifications we control for additional variables X, typically fixed effects for the revenue district and parliamentary constituency. The Calonico et al. (2014) estimator has trouble calculating an optimal bandwidth while controlling for these fixed effects. We instead use the optimal bandwidth calculated for the analogous regression with no fixed effects and use that bandwidth in the other specifications.

4.3.2 Difference-in-Discontinuities

When testing for mechanisms we also estimate a "difference-in-discontinuity" specification that measures how the *difference* in allocations across areas *within a panchayat* changes when the AITC gains control of the panchayat. Panchayats are divided into administrative units called "villages." Let v index a village within panchayat k. We estimate a difference-in-discontinuity specification

$$Y_{kvt} = \alpha_k + \phi_1 d_k s_{kv} + \phi_2 d_k M_k s_{kv} + \beta M_k s_{kv} + \varepsilon_{kvt} \qquad \text{for } k \text{ such that } |d_k| < h \tag{10}$$

where is α_k is a panchayat fixed-effect. The main effect of the running variable and the dummy for AITC control are absorbed into the panchayat fixed-effect. What remains is the interaction of these terms with s_{kv}, which is either a proxy for a village's historical support for the AITC or the actual vote share of the AITC candidate in the 2014 national election. In some specifications we will test for whether s_{kv} is a proxy for some other variable by controlling for the difference-in-discontinuity induced by some control variable X_k :

$$\begin{aligned} Y_{kvt} = \alpha_k &+ \phi_1 d_k s_{kv} + \phi_2 d_k M_k s_{kv} + \beta M_k s_{kv} && (11) \\ &+ \phi_3 d_k X_{kv} + \phi_4 d_k M_k X_{kv} + \phi_5 M_k X_{kv} + \varepsilon_{kvt} \qquad \text{for } k \text{ such that } |d_k| < h && (12) \end{aligned}$$

We cluster standard errors by panchayat. As we are unaware of any method to estimate the optimal bandwidth in a difference-in-discontinuities specification, we instead apply the method of Calonico et al. (2014) to the village-level analog of Equation 9.[14]

4.3.3 Biggest Party

We disentangle the impact of being the biggest party versus holding the absolute majority by constructing a measure of "distance" to the cutoff where the AITC becomes the biggest party. There are many complications to defining this measure. The number of seats needed for an absolute majority is fixed given the total seats on the council. But the number of seats needed to be the "biggest party" depends on the number of seats won by the other parties, and the distance depends which party is counterfactually losing votes to the AITC.[15] Given the ambiguities we define only the infinity-norm. We incrementally switch seats from the AITC to the runner-up in the race until the AITC is no longer the biggest party. We then measure the largest margin among the set of seats that were hypothetically switched.

Even given this running variable we cannot estimate a regression discontinuity because in most cases when the AITC switches to being the biggest party it also gains the absolute majority. We cannot simply drop the cases where the AITC has the absolute majority because that would create sample selection at the discontinuity. To disentangle the effects we instead estimate ordinary least squares regressions of each outcome on a dummy for whether the AITC is the biggest party while controlling for whether it holds the absolute majority. To avoid comparing cases that are too dissimilar we restrict attention to a window of observations where the distance to "biggest party" is small. To the extent that observations are dissimilar it will bias estimates upwards (especially those on vote returns), which cuts against our hypothesis.

Let $\tilde{d}_k$ be the distance to the number of seats where the AITC becomes the biggest party, and $\tilde{M}_k$ be a dummy for whether the AITC is the biggest party in the panchayat council. As before, M_k

[14] Likewise, we are unaware of any method to estimate bandwidth-robust p-values for a difference-in-discontinuities.

[15] Take a simple example where the AITC wins 5 seats, the CPM wins 4 seats, and the BJP wins 3. It may seem that the "distance" to minor party status is just the vote share of the 1 seat where the AITC won the fewest votes. But that assumes the runner-up in that contest was the CPM. If the runner-up was the BJP the assumption does not hold.

is a dummy for whether the AITC also holds the absolute majority. We estimate the regression:

$$Y_k = \phi_0 + \beta' \tilde{M}_k + \beta M_k + \varepsilon_k \qquad \text{for } k \text{ such that } |\tilde{d}_k| < h \tag{13}$$

We estimate this regression for several choices of h to confirm that the results are robust.

5 Main Results

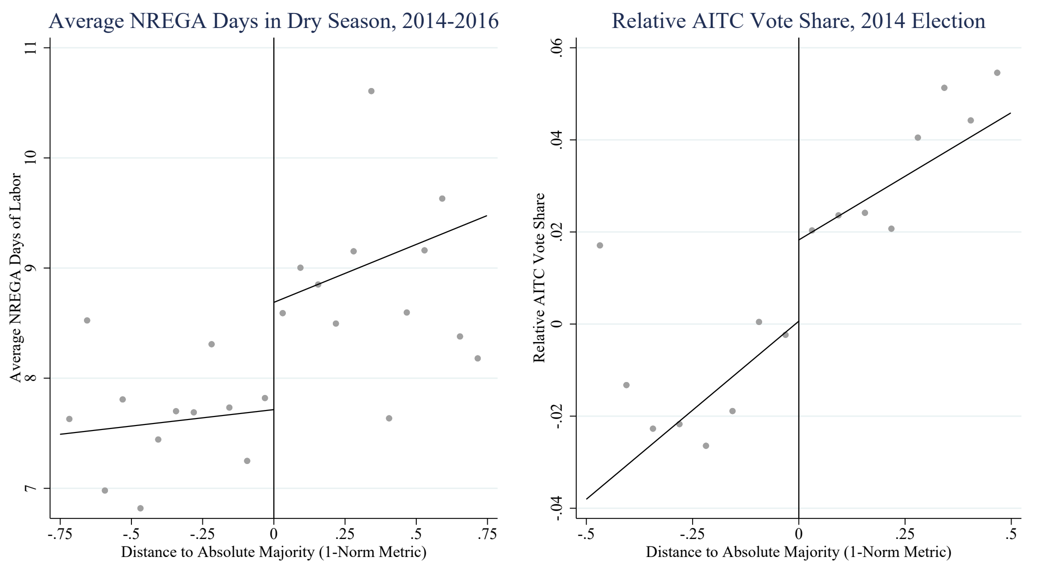
5.1 State Government Allocates Disproportionate Funds to Co-Partisan Panchayats

The left-hand panel of Figure 2 shows the regression discontinuity with the 1-norm as the running variable and the NREGA job allocation of the average household as the outcome, pooling outcomes across years $t = 2014, 2015, 2016$. The figure shows allocations during the dry season, the first three months of the year, when the demand for NREGA jobs is at its peak. When the 1-norm switches from negative to positive the AITC switches to holding an absolute majority in the panchayat council after the 2013 local election. The figure implies that the average household in an AITC-controlled panchayat receives roughly 1 more day of NREGA labor (9 days versus 8 days—see Column 1 of Table 1).

Table 1 confirms that this result holds across several specifications. Column 1, which is the same specification as Figure 2, estimates (9) without controls. Column 2 shows that the coefficient is largely unchanged by adding district and constituency fixed effects. Columns 3–4 show that the estimates are almost identical when the running variable is the 2-norm (Euclidean distance) and the infinity-norm.

While columns 1–4 of Table 1 pool the post-election years 2014 to 2016, columns 5–7 report the specification from Column 2 separately by year. The premium for AITC-controlled panchayats is biggest in 2014, the year of the national election, but still systematically higher in 2015 (when there is no election). The effect is noisier and only marginally significant in 2016, possibly for the reasons we explore in Section 7. The dry season results are especially informative both because the need for poverty relief is high and because the 2014 dry season was immediately before the national election. But Column 8 shows similar impacts on average allocations for the full year.

Figure 2
AITC-Controlled Panchayats Get More NREGA Labor and Subsequently Return More Votes for the AITC in the 2014 National Election



Note: Outcome is the panchayat-level average NREGA household allocation, pooling data from 2014-2016 (analogous to Column 1 of Table 1). Each dot shows the average of the outcome within a bin of width 6.25 percentage points in the taxi metric. The observations are restricted to the optimal bandwidth (rounded to the nearest bin). The linear predictions are generated using a triangular kernel.

5.2 Panchyats Controlled by Ruling Party Return More Votes for its National Candidates

We estimate Equation 9 to test whether AITC-controlled panchayats also returned more votes for the party's candidate in the 2014 national election. We calculate the average vote share of the AITC candidate within each panchayat and define the "AITC Lean" of a panchayat as the share of AITC votes within the panchayat minus the overall share received by the candidate in the entire parliamentary constituency. We estimate Equation 9 on the vote lean using several specifications.

The right-hand panel of Figure 2 visualizes the impact of AITC control of the local council on the AITC lean. Control of the council yields roughly 2 percentage points more votes for the AITC's parliamentary candidate during the 2014 election. Table 2 confirms these results using several specifications. Column 1 is the same specification as the figure. Column 2 shows that this estimate is largely unchanged when we control for district and constituency fixed effects.

Table 1
Panchayats Under AITC Control Receive Larger Per-Household NREGA Allocations

	Dry Season							Full Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	All	All	All	2014	2015	2016	All
RD Estimate	0.979***	1.068***	1.111***	1.181***	1.482***	0.735***	0.842*	1.983***
	(0.354)	(0.292)	(0.348)	(0.387)	(0.464)	(0.278)	(0.461)	(0.604)
Obs in BW	4200	4200	3963	3843	1326	1307	1294	4323
Clusters in BW	1400	1400	1321	1281	1326	1307	1294	1441
Control Mean	7.83	7.83	7.56	7.73	10.61	2.73	10.55	20.05
Bandwidth	0.775	0.775	0.282	0.169	0.583	0.549	0.521	0.898
Robust p-val	0.008	0.015	0.031	0.033	0.103	0.011	0.173	0.028
Metric	1-Norm	1-Norm	2-Norm	Inf-Norm	1-Norm	1-Norm	1-Norm	1-Norm
District FEs		X	X	X	X	X	X	X
Constituency FEs		X	X	X	X	X	X	X

Note: The table shows RD estimates of Equation 9. The outcome in all columns is the average per-household days of labor, where the average is over all job cards in the panchayat. Columns 1—7 measure the average over the dry season (first three months of the year) while Column 8 averages over the entire year. Columns 1–4 and Column 8 pool observations across the years 2014–2016, while columns 5—7 restrict to a single year. Bandwidths are calculated using the method of Calonico et al. (2014) on the equivalent specification without fixed-effects (see text for details). "Robust p-val" gives the p-value after adjusting for bandwidth uncertainty. "Metric" gives the distance metric (to AITC absolute majority) used as the running variable. Standard errors are clustered within panchayat. See text for description of each specification.
*p=0.10 **p=0.05 ***p=0.01

Column 3 shows that using the raw AITC share (without netting out the party's overall share in the constituency) yields nearly identical coefficients. Column 4 shows the results are unchanged when the vote share is calculated after discarding polling stations within the panchayat where some job card holders are registered to vote in a different parliamentary constituency. Columns 5 and 6 show that the estimates are almost identical when the running variable is the 2-norm and the infinity-norm.

5.3 The Results are Driven by Co-Partisan Control, Not Just Co-Partisan Officials

Co-partisan areas could receive higher NREGA allocations for any number of reasons. There could be efficiencies that arise from partisan alignment because there is less asymmetric information, or because state officials can more easily force co-partisan council presidents to put in the effort of proposing NREGA projects. It is also possible that there is a desire to elevate intra-factional allies, as proposed by Persico et al. (2011). Separately, it is possible that co-partisan areas return votes at a higher rate solely because the council president endorses her party's na-

Table 2
Impact on 2014 National Election

	(1) AITC Lean	(2) AITC Lean	(3) Raw AITC Share	(4) Hom. AITC Lean	(5) AITC Lean	(6) AITC Lean
RD Estimate	0.017***	0.021***	0.020***	0.021***	0.018***	0.018***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Obs in BW	1263	1263	1129	1265	1282	1128
Bandwidth	0.480	0.480	0.329	0.483	0.261	0.127
Robust p-val	0.010	0.002	0.002	0.003	0.007	0.031
Metric	1-Norm	1-Norm	1-Norm	1-Norm	2-Norm	Inf-Norm
District FEs		X	X	X	X	X
Constituency FEs		X	X	X	X	X

Note: "Robust p-val" gives the p-value after adjusting for bandwidth uncertainty (see Calonico et al., 2014). "Metric" gives the distance metric (to AITC absolute majority) used as the running variable. Bandwidths are MSE-optimal. Standard errors are calculated using 3 nearest neighbors (as each panchayat is observed only once, clustering is unnecessary). See text for description of each specification.
*p=0.10 **p=0.05 ***p=0.01

tional candidate.

What distinguishes these models from ours is that the other models predict impacts driven solely by *whether the council president is from the ruling party*. Our model requires that the party have unchecked control over the targeting of NREGA benefits. The local institutions in West Bengal provide a crucial test between the competing models because it is possible for the AITC to hold the presidency *without having unchecked control*. As in many parliamentary systems, any would-be president must be backed by a majority of elected council members. But since most panchayats have multiple competing parties, in some panchayat councils the AITC wins the most seats but falls short of an absolute majority, forcing it to form a coalition. By convention the largest party almost always has the first chance to form a coalition. Hence the party of the president will generally be from the AITC regardless of whether it has a majority or is merely the largest party. The difference is that when the AITC holds an absolute majority there is no institutional check, whereas when it is only the largest party its coalition partner can threaten to bring down the government. This threat can prevent the AITC from targeting NREGA jobs for political gain.

Table 3 estimates Equation 13 within three different windows around the cutoff where the AITC switches from being a minor party to being the biggest party (where the window is defined using the minimal swing distance explained in Section 4.3). Columns 1—3 show that, across a

Table 3
Impact of Absolute Majority Versus Coalition

	AITC President			NREGA Days			Vote Lean		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Biggest Party	0.452***	0.431***	0.315***	-0.119	-0.807	-1.155	0.014**	0.008	-0.002
	(0.044)	(0.047)	(0.058)	(0.564)	(0.589)	(0.703)	(0.006)	(0.007)	(0.007)
Majority	0.346***	0.340***	0.391***	2.367***	2.612***	2.514***	0.023***	0.024***	0.026***
	(0.040)	(0.041)	(0.049)	(0.569)	(0.597)	(0.738)	(0.006)	(0.006)	(0.007)
Obs.	1026	845	496	1214	989	588	1214	989	588
Control Mean	0.192	0.216	0.278	9.747	10.144	10.209	-0.014	-0.010	-0.002
Window	0.15	0.10	0.05	0.15	0.10	0.05	0.15	0.10	0.05

Note: Each column estimates Equation 13 on a different outcome and a different window h. "Biggest Party" is a binary variable equal to one when the AITC has strictly more seats than any other party. "Majority" likewise equals one when the AITC holds an absolute majority of seats. The variables are not mutually exclusive. If "Biggest Party" equals zero then "Majority" must equal zero. Thus the coefficient on "Largest Party" estimates the impact of being the biggest party without an absolute majority, and "Absolute Majority" estimates the additional impact of holding the absolute majority. "AITC President" is a binary variable equal to one when the council president is a member of the AITC. "NREGA Days" gives the average per household NREGA days during the 2014 dry season. "Vote Lean" is as defined in Table 2.
*p=0.10 **p=0.05 ***p=0.01

range of windows, becoming the largest party raises the probability of an AITC council president by 30 to 45 percent. The point estimate implies a doubling or tripling over the baseline where the AITC is a minor party. The *additional* impact of also having an absolute majority is of a similar magnitude. Together these coefficients suggest that even when the AITC does not hold the absolute majority, simply being the biggest party more than doubles the chance of an AITC president.

But Columns 4—6 show no evidence of an accompanying increase in the aggregate NREGA allocation. Only when the AITC has the majority does the panchayat receive more days of NREGA labor. Columns 7—9 show a similar pattern for the AITC lean of the 2014 election returns. Only at the widest window is there any evidence that being the biggest party increases votes. The effect vanishes as the window narrows, suggesting it is caused by selection bias. The effect of holding the majority is by contrast consistently positive and significant.

In summary, panchayats where the AITC is the biggest party are substantially more likely to have an AITC president but receive no more NREGA jobs and return no more votes for the AITC. Only panchayats where the party holds the absolute majority, and thus faces no external check on its control of the council, receive extra NREGA jobs and return additional votes. These results are inconsistent with models of co-partisan efficiency and simple partisan favoritism, but they are consistent with our model of political complementarities.

6 Mechanism

6.1 There is Political Targeting Within the Panchayat

Section 5 shows that the state targets NREGA allocations to co-partisan panchayats, but not in the way predicted by simple models of partisan favoritism. A further distinction of our model is that the state over-allocates funds to co-partisan local councils because it knows they will use the funds for political targeting within the panchayat. Is there evidence of within-panchayat political targeting?

For obvious reasons we cannot observe individual votes, but we can measure votes by 'village,' a sub-panchayat administrative unit with a median size of 200 households. We test whether *within a panchayat*, villages that have historically voted for the AITC are disproportionately rewarded when it controls the panchayat council. We estimate Equation 10, the difference-in-discontinuities. We interact the dummy for AITC control with three measures of past political support: the average 2013 share of AITC candidates in the village, the AITC vote share in the 2011 election, and the average of these two measures.

Columns 1—5 of Table 4.a show the difference-in-discontinuity estimates for allocations during the dry season. The first three columns imply that when the AITC controls the local council, pro-AITC villages (based on all three measures of historical support) get systematically higher NREGA allocations in the 2014 dry season. Column 4 shows similar albeit weaker patterns for the full 2014-to-2016 stretch. Targeting in later years is thus no longer as strongly linked to pre-2014 support (either because there is less targeting in non-election years, or because they have the 2014 vote share as a more current guide to political support). Column 5 shows that the result holds even after controlling for whether there is an elected AITC official living in the village, suggesting historical support is not just a proxy for electing an AITC candidate. Column 6 shows similar effects for the full year of allocations.

Could these measures of past support simply be proxying for demographic characteristics that are correlated with objective need for poverty relief? We test this alternative interpretation by calculating for each panchayat the average days of labor per household within each of several demographic characteristics: Scheduled Caste/Tribe versus Other Caste, Muslim versus Non-Muslim, and Below versus Above Poverty Line. We take the difference between the average within each category and the overall average within the panchayat. This difference represents the excess allocation to this group. If AITC-controlled panchayats are simply targeting low income households, we would expect the excess allocation for Scheduled Castes and Tribes, Muslims, and Below-Poverty-Line households to increase at the cutoff. Table 4.b shows that this is not the case. There is no evidence of targeting to disadvantaged demographics.

6.2 AITC Candidates Receive Excess NREGA Payments

Trilateral coordination requires local officials to exert effort on behalf of a national candidate who has no official authority over them. Even a successful candidate has relatively little personal power to reward that effort. The organization must somehow sustain local cooperation. One possible means is through direct payments through NREGA itself. Since we observe beneficiary names in the NREGA administrative dataset, we can match the candidates standing for election in the 2013 election to their NREGA job card profiles. We use this measure to test whether AITC local candidates receive more generous payouts when the AITC controls the council.

We estimate Equation 9 on the average days of labor within the subset of households of AITC candidates. For comparison we estimate the same equation for all other households in the panchayat. Columns 1—4 of Table 5 show that while both sets of households receive higher dry season NREGA allocations under AITC control, the point estimate for AITC candidates is twice as large. Columns 5—8 show that the difference is even bigger when we measure allocations over the entire year. All specifications show bigger RD estimates for AITC candidates than other households. We test for whether the difference is statistically significant using a nonparametric clustered bootstrap. The p-value is roughly 0.06 for dry season allocations and less than 0.01 for allocations over the entire year.

One natural objection to this test is that it may reflect personal corruption by the individuals in power rather than a payment by the party. Though councilors other than the president have

Table 4
Targeting

a) There is Targeting by Political Affiliation...

	Dry Season					Full Year
	(1)	(2)	(3)	(4)	(5)	(6)
	2014	2014	2014	2014-2016	2014	2014
Majority X GPSHARE	4.953**					
	(2.446)					
Majority X AITC2011		5.594*				
		(3.144)				
Majority X AVERAGE			5.022***	1.851*	4.312**	9.382***
			(1.938)	(1.008)	(1.990)	(3.581)
Majority X AITC REP					0.484	
					(0.461)	
Obs in BW	6637	7696	11107	34986	11107	10929
Clusters	1325	1160	1323	1398	1323	1303
Bandwidth	0.789	0.572	0.588	0.766	0.588	0.550
Metric	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm
Panchayat FEs	X	X	X	X	X	X

b) ...Not by Proxies for Poverty or Need

	Caste Group			Religion		Below/Above Poverty Line	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SC	ST	Other	Muslim	Non-Muslim	Below	Above
RD Estimate	0.156	-0.275	0.096	0.331	0.099	-0.594	-0.023
	(0.285)	(0.664)	(0.128)	(0.485)	(0.062)	(0.411)	(0.057)
Obs in BW	1347	1108	1308	1293	1297	1307	1424
Clusters in BW	1347	1108	1308	1293	1297	1307	1424
Bandwidth	0.64	0.47	0.56	0.56	0.53	0.65	0.84
Robust p-val	0.536	0.732	0.850	0.368	0.406	0.133	0.996
Metric	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm
District FEs	X	X	X	X	X	X	X
Constituency FEs	X	X	X	X	X	X	X

Note: **a)** The table shows estimates of Equation 10. "Metric" gives the distance metric (to AITC absolute majority) used as the running variable. Bandwidths are calculated using the method outlined in Section 4.3. The unit of observation is a village-year, and standard errors are clustered by panchayat. "AITC2011" refers to AITC vote share in 2011 state election, "GPSHARE" to the average vote share of all resident AITC candidates in the 2013 local election, and "AVERAGE" to the average of these two measures (if one of them is not observed for a village, "AVERAGE" simply equals the other measure—hence that specification has the most observations). "AITC REP" is a dummy for whether the village is home to an elected AITC council member. **b)** We estimate Equation 9 on the excess days of labor allocated to each demographic group ("SC" and "ST" abbreviate Scheduled Caste and Scheduled Tribe). The outcome is the average days of labor per household within the sub-population minus the overall average for the panchayat. All averages are for the 2014 dry season. *p=0.10 **p=0.05 ***p=0.01

Table 5
AITC Candidates Receive Excess Payments

	Dry Season				Full Year			
	(1) AITC Cand.	(2) Other HH	(3) AITC Cand.	(4) Other HH	(5) AITC Cand.	(6) Other HH	(7) AITC Cand.	(8) Other HH
RD Estimate	2.046***	0.994***	2.094***	1.086***	4.917***	1.792**	5.317***	2.025***
	(0.602)	(0.343)	(0.538)	(0.283)	(1.401)	(0.783)	(1.220)	(0.628)
Obs in BW	3798	4293	3798	4293	3990	4140	3990	4140
Clusters in BW	1266	1431	1266	1431	1330	1380	1330	1380
Bandwidth	0.499	0.917	0.499	0.917	0.624	0.751	0.624	0.751
Robust p-val	0.0028	0.0053	0.0444	0.0059	0.0011	0.0335	0.0026	0.0616
Metric	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm
District FEs			X	X			X	X
Constituency FEs			X	X			X	X
P-val: Difference		0.0604		0.0602		0.0054		0.0076

Note: We estimate Equation 9 for average payments to households of AITC candidates and all other households. “Metric” gives the distance metric (to AITC absolute majority) used as the running variable. Bandwidths are calculated using the Calonico et al. (2014) method. Standard errors are clustered within panchayat. “P-val: Difference” tests for whether the coefficients in adjacent columns are significantly different (the value in Column 2, for example, tests for the difference between RD Estimates in Columns 1 and 2). The test is run using a clustered bootstrap that nonparametrically accounts for the uncertainty in the choice in bandwidth.
*p=0.10 **p=0.05 ***p=0.01

no formal authority over NREGA allocations, one can imagine a deal where the president buys off the other members of the council to keep everyone complicit in the misdirection of funds. We test this possibility by splitting the AITC candidates into those that won their seat on the council and those that did not, and estimating the discontinuity separately for each. Table 6 shows that the increase in benefits is very similar for winners and losers, both for the dry season and the full year. Since losers have no direct control over the program, these excess payments could only happen with the complicity of the party apparatus. That is consistent with the idea that the payments are in return for maintaining, organizing, and delivering votes rather than serving in office. In unreported results we also find that the AITC council president’s payments on average are roughly equal to those of a regular AITC council member, reinforcing that the payments are not linked to their position on the council.

One concern given these results is that the AITC rewards all of its voters, and being an AITC candidate is just a proxy for being an AITC voter. In Appendix B.2 we show that even in villages where more than 50 percent of people voted for the AITC, the median household does not receive a premium under AITC control anywhere close to that enjoyed by AITC candidates.

Table 6
Payment is Similar for Winning and Losing Candidates

	Dry Season				Full Year			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser
RD Estimate	1.764**	1.778**	1.822***	1.798**	3.726*	3.739**	4.098**	4.147***
	(0.757)	(0.778)	(0.692)	(0.729)	(1.957)	(1.777)	(1.750)	(1.598)
Obs in BW	3690	3276	3690	3276	3474	3471	3474	3471
Clusters in BW	1230	1092	1230	1092	1158	1157	1158	1157
Bandwidth	0.590	0.427	0.590	0.427	0.451	0.547	0.451	0.547
Robust p-val	0.033	0.053	0.353	0.032	0.069	0.064	0.326	0.020
Metric	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm
District FEs			X	X			X	X
Constituency FEs			X	X			X	X

Note: We estimate Equation 9 for average payments to households of winning AITC candidates and losing AITC candidates. "Metric" gives the distance metric (to AITC absolute majority) used as the running variable. Bandwidths are calculated using the Calonico et al. (2014) method. Standard errors are clustered within panchayat.
*p=0.10 **p=0.05 ***p=0.01

6.3 Candidates Who Muster More Votes Receive Bigger Post-Election Payouts

Fixed payments would be sufficient to sustain the cooperation of local officials, but can they induce effort? If state officials cannot observe some key features of the local official's electioneering—whether they are targeting jobs to the right voters, for example—a fixed payment may no longer be optimal. Organization theory predicts the optimal contract will include some incentive pay (Hölmstrom, 1979). Recent anecdotal and historical evidence suggests party bosses may behave similarly.[16]

We test this hypothesis by estimating the difference-in-discontinuities (Equation 10) on the village-level average payments to AITC candidates *in the 4 weeks immediately after the 2014 election*. We interact the discontinuity with the AITC vote share in the village. Column 1 of Table 7 shows that, after controlling for panchayat fixed effects, AITC candidates receive an extra 1 day of labor for every additional 6.6 percentage points returned by their village for the AITC's national candidate.[17] Column 2 shows that the 2014 vote share is not simply a proxy for whether the vil-

[16] For example, Novaes (2018) describes how parties in Brazil maintain spreadsheets that record the vote returns in each local candidate's territory alongside the payments they will receive. A recent analysis of a similar set of accounts maintained by a 1950s-era Brazilian congressman shows a positive correlation between payments and the number of votes delivered in excess of prior performance (Gingerich, 2020).

[17] $6.6 = 1/15.198 \times 100$

lage elected an AITC candidate. We simultaneously control for the difference-in-discontinuity between villages that do and do not have at least one "Winning AITC Cand." by estimating Equation 11. Our coefficient of interest is unchanged.

Table 7
Candidates Whose Villages Return More Votes Receive More Pay in the 4 Weeks After the 2014 Polling Date

	(1) 2014	(2) 2014	(3) 2014	(4) 2014	(5) 2014	(6) 2014	(7) 2014	(8) 2015 (Placebo)
AITC Majority								
X 2014 Vote Share	15.198***	14.685***	14.537***	6.905	10.128*	14.490***	12.465***	-0.149
	(4.723)	(4.848)	(5.020)	(6.100)	(6.090)	(5.190)	(4.815)	(3.408)
X Winning AITC Cand.		0.248	0.318	0.876	0.849	0.215	0.100	
		(0.764)	(0.891)	(0.892)	(0.887)	(0.774)	(0.767)	
X 2013 AITC Share			-0.557					
			(4.452)					
X 2011 AITC Share				8.022				
				(5.961)				
X 2009 AITC Share					0.638			
					(5.605)			
X Avg. Past Share						0.007	-0.760	
						(5.704)	(5.059)	
X Non-Cand. Days							0.250	
							(0.242)	
Villages in BW	3523	3552	3602	2774	2777	3590	3521	3660
Panchayats in BW	898	905	920	787	787	915	898	936
Bandwidth	0.471	0.483	0.509	0.606	0.592	0.498	0.508	0.552
Panchayat FEs	X	X	X	X	X	X	X	X

Note: Estimates are from within-panchayat regressions where the unit of observation is a village. The outcome is the average NREGA payments to all AITC candidates in the village in the 4 weeks after the date of polling in the 2014 election. The key regressor of interest is the village's 2014 AITC vote share. Columns 1—4 are OLS regressions restricted to panchayats within 0.1 of the cutoff based on the 1-norm. Column 5 is a difference-in-discontinuities regression where the bandwidth is chosen by applying the method of Calonico et al. (2014) to a basic RDD framework with village-level observations. Standard errors are clustered by panchayat. See text for description of each specification.
*p=0.10 **p=0.05 ***p=0.01

Columns 3—6 add similar controls for the average vote share of AITC candidates in the 2013 local election, the vote share in the 2011 state election, the 2009 national election, and the average across all three elections. The results are qualitatively similar, though the estimate in Column 4 is somewhat smaller and it loses significance. That may be driven by the reduction in sample size (as we are unable to link some 2011 polling stations to a village, and vice-versa). It may also suggest the payment is partly backward-looking, as might be true if the candidate is paid in part for the effort of maintaining an existing bloc of voters.

Could these patterns arise because the entire village is rewarded for favoring the AITC, and some of the largess passes through to local candidates? One very basic test for this hypothesis is to add a difference-in-discontinuity control for the average days of labor awarded to non-candidates.[18] Column 7 shows that the coefficient of interest remains largely unchanged.

Are these correlations actually related to the election, or could they reflect some other characteristic of the village or the candidates who live there? One very basic placebo test is to estimate (10) on the average NREGA allocations to AITC candidates *during the same 4 calendar weeks in 2015*, when there was no election. Column 8 shows that there is no similar effect on 2015 allocations, supporting the idea that the payments are linked specifically to the 2014 election.

7 Horizontal Expansion: Recruiting Majorities in Local Councils

7.1 Candidates Systematically Switch to the Ruling Party

If control of state and local government are complements, the state ruling party has a strong incentive to take control of more local councils. The party would gain the power to target and claim credit for NREGA jobs. It could of course win control of these councils in the next local election. But a quicker approach is to recruit members of the opposition. Complementary control also implies that the ruling party has more to offer an elected local councilor than the opposition through its control of NREGA projects. Is there evidence that opposition candidates defect to the ruling party?

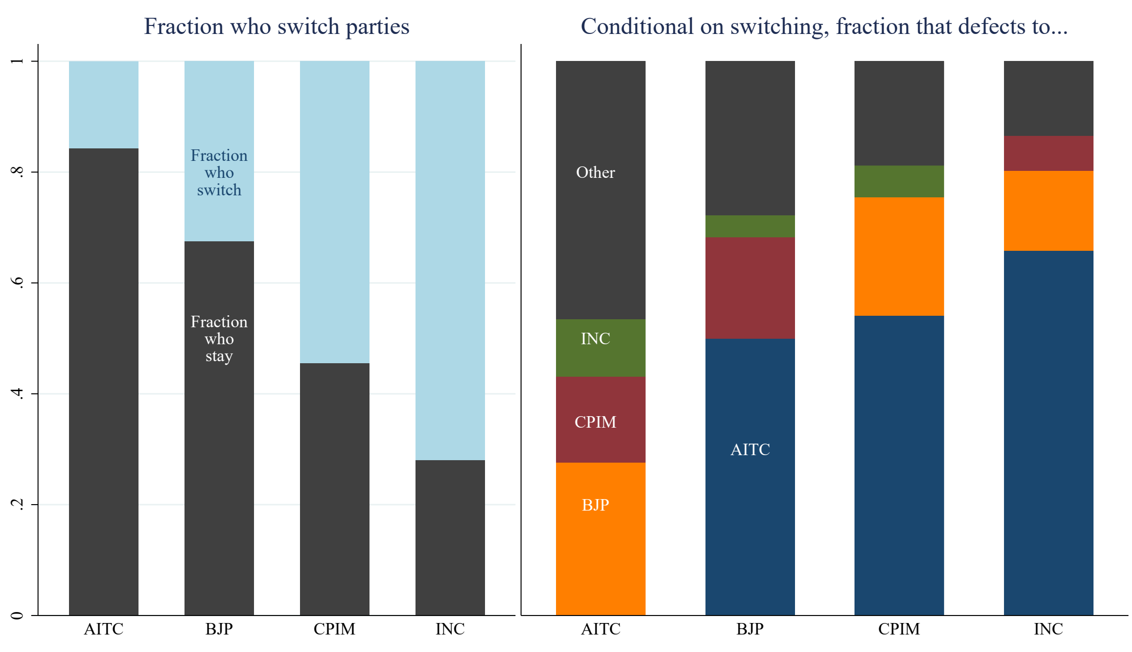
There is no official record of whether a local candidate has changed her allegiance. Instead we link candidates for the 2013 local election by name and panchayat to candidates in the subsequent 2018 local election. Within the subset of candidates who stood for office in both years, we infer that a candidate has "switched" allegiance if they register under a different party. For example, if we observe Abhishek Chatterjee contesting in 2013 as a member of the Communist Party-Marxist (CPIM) but in 2018 as a member of the AITC, we infer he has switched from the CPIM to the AITC. Likewise, we infer that a candidate has "stayed" with their party if they register

[18] To be precise we now include both the average vote share across past elections and the average non-candidate allocation to the vector X.

under the same party in both elections.

Figure 3

Candidates are Far More Likely to Leave Opposition Parties than the Ruling Party



Note: Among the set of candidates standing for election in both 2013 and 2018, the left-hand panel shows the fraction who "stay" registered with the same party in 2018 as in 2013 versus those who "switch" their 2013 party to register with a different party (or as an independent) in 2018. Each fraction is calculated among candidates registered in 2013 with the ruling party (AITC), the Bharatya Janata Party (BJP), the Communist Party-Marxist (CPIM), and the Indian National Congress (INC). The right-hand panel shows which parties candidates are switching into (conditional on switching). "Other" refers to minor parties and independents.

The left-hand panel of Figure 3 shows the probability of switching versus staying conditional on the candidate's 2013 party registration. Over 80 percent of the AITC's candidates remain with the AITC—by far the highest retention rate of any major party in West Bengal. By contrast, both the CPIM and the Indian National Congress (INC) lose the majority of their candidates. The INC in particular loses over 70 percent of its candidates to other parties.

The right-hand panel of Figure 3 shows where, conditional on switching, these candidates choose to go. The AITC's own relatively small pool of defectors tend to switch to either a minor party or the Bharatiya Janata Party (BJP). That is not surprising because after 2014 only the BJP has the resources to compete with the AITC.[19] But among all other parties the switchers overwhelmingly join the AITC, suggesting it is stealing many of these parties' candidates. In un-

19 Outside of West Bengal, the BJP won a massive victory in the 2014 national election. This victory, largely at the expense of the INC, gives the BJP resources unavailable to the other parties.

reported results we also find that defectors from the opposition parties tend to be their most popular candidates, meaning those who earned the most votes in the 2013 local election. The opposition is thus left with fewer and less effective organizers.

7.2 Candidates who Switch to or Stay With the Ruling Party Get Bigger Payments

What induces these opposition candidates to forswear their old allegiances? Though it is possible they are persuaded by ideology or a simple desire to be on the winning side, anecdotal accounts suggest money may be part of the answer. There are countless reports of politicians at all levels of government taking bribes to switch parties.[20] We can look for direct evidence of such payments by measuring the average 2015 NREGA allocations to all AITC candidates who live in the village. We focus on 2015 because, as the next section implies, the year between the 2014 national election and the 2016 state election is crucial.

Figure 4.a shows that candidates who stay with the AITC receive far larger NREGA allocations in 2015 than candidates who stay with any other party (the gap ranges from 8 to 13 days). More importantly, candidates who switch from the AITC between 2013 and 2018 receive far smaller allocations than those who remain (roughly 8.5 days fewer). By contrast, payments to candidates who leave the two main opposition parties (the CPIM and the INC) to join the AITC are higher than those to candidates who either stay or who switch to a party other than the AITC.[21] If our hypothesis is true—that the ruling party is seeking recruits who can help it take control of a local council—we would expect the extra payments would accrue mainly to candidates who actually won their races and thus have a vote on the council. Figure 4.b shows that, at least for the two main opposition parties, the gap in payments between stayers and switchers appears only for winning candidates.

By themselves these results do not prove that the payments induced candidates to switch.

[20] A few recent examples: 'BJP Offered Bribe to Congress MLAs to Switch Sides in Gujarat: Congress', Hindustan Times, October 18, 2020; 'On MLA's "35-Crore Bribe" Claim, Sachin Pilot Says "Vexatious, Concocted"', NDTV, July 20, 2020; 'Why Minister Eshwarappa's Letter Has Dealt 'Unprecedented' Blow to Already Troubled Yediyurappa', The Print, April 2, 2021.

[21] The differences between payments to stayers in the three opposition parties versus stayers in the AITC are all highly significant (at the 1 percent level). The difference between switchers and stayers in the AITC is also significant at the 1 percent level. The difference between members of the INC and CPIM who stay versus those who switch to the AITC is also significant.

It is possible they switched for other reasons and simply started receiving larger payments as part of the package. But the pattern is at least consistent with a higher return to staying in the AITC or switching to the AITC (at least for candidates originally aligned with the INC). The gap between stayers and leavers in the AITC, for example, translates to a difference of over 1400 rupees, roughly 30 percent of the monthly consumption expenditure of the median household in rural West Bengal.[22]

7.3 Switching to the Ruling Party is Most Common in Panchayats where the Ruling Party Falls Short of a Majority

Does the party switching represent actual strategic recruitment by the ruling party, or mere one-sided opportunism by candidates who are switching party without necessarily being invited or courted by the ruling party? Figure 4.b offers some evidence that only switching candidates with something to offer (a vote on the council) get a premium through NREGA payments. But a more direct test is to see whether the net inflow of candidates switching to the AITC is highest in the areas where it actually needs more votes on the council to gain the absolute majority.

Figure 5.a graphs the average net influx of candidates to the AITC—that is, the number of opposition candidates switching to the AITC minus the number of AITC candidates switching to a different party—against the margin of seats it won in the 2013 election. Where the margin is negative the AITC needs additional votes for the absolute majority. Where it is zero or positive the AITC won enough seats for the majority without any need for post-election recruitment. The figure shows that the average net influx is on average positive only in areas where the party needs seats. In areas where it has enough seats the average is close to zero. This pattern is striking because it is in the areas where the AITC has control that an opposition candidate has the most to gain from a unilateral switch to the AITC. But these are also the areas where the hypothetical recruit has relatively little to offer in return.

[22] According to the 2014-2015 National Survey Sample dataset.

7.4 By 2016, Panchayats Barely Won and Barely Lost in 2013 Vote for the Ruling Party at Similar Rates

If the ruling party is using recruitment to systematically take over councils it did not previously control, it would be better positioned in those areas to contest future elections. Such changes would be most obvious in the neighborhood of the cutoff for an absolute majority as measured with the running variable, which was defined based on the 2013 local election without adjustment for subsequent recruitment. The left-hand panel of Figure 5.b is similar to 5.a, except it plots the net influx as a function of the running variable. We divide the running variable into bins of width 0.15 (the bins must be relatively wide because the outcome is noisy). We calculate the average net gains for the AITC across all panchayats within the bin. We restrict our sample to the panchayats within a distance of 0.6 in the 1-norm metric.

The figure shows that the AITC is most likely to gain members on the "control" (negative) side of the cutoff. On this side of the cutoff, the size of the average gain is proportional to the distance from the cutoff. [23] By contrast, there is no obvious pattern on the "treated" side of the cutoff. The pattern is not surprising given Panel a, but plotting the net influx against the running variable clarifies that the party's recruitment over the period from 2013 to 2018 effectively converts "control" panchayats into "treated" panchayats. The recruitment did not happen immediately after the 2013 local elections, for if they had then the regression discontinuity estimates in Table 2 would have found that winning an absolute majority in 2013 would have had no impact on the national election of 2014.

But we can get some suggestive evidence of the medium-run impact of recruitment by applying the same test to the returns from a state election in 2016. The 2016 election pitted the same major parties in a contest for control of the state assembly of West Bengal, making the stakes even higher for the ruling party. Much as we did for the 2014 national election, we match polling stations to panchayats and measure the percentage of votes received by the AITC's state

[23] This is only a rough intuition because the taxi metric depends not only on the number of seats but the margin by which the seats were lost. The party would presumably care about both when making recruitments (all else equal it would prefer to recruit popular candidates with many followers), but it is not obvious how it would weigh the quality of new recruits against the simple calculus of how many seats are needed for a majority. The taxi metric itself effectively treats two seats lost by 10 percent and 1 seat lost by 20 percent as equally distant from the cutoff even though the party may not.

assembly candidate (relative to the candidate's overall share in the whole constituency for that assembly seat).

The right-hand panel of Figure 5 plots the regression discontinuity in the AITC lean for both the 2014 and 2016 election. To put the elections on a similar axis we first strip out district and parliamentary constituency fixed-effects, making this the same specification as Column 2 of Table 2.[24] For each election we restrict observations to the optimal bandwidth and plot the linear prediction alongside the average of the outcome within 12 equally spaced bins.

The figure shows that the discontinuity in 2014 election returns has vanished by 2016. Panchayats where the AITC barely won an absolute majority in the 2013 local elections return no more votes than those where it barely lost. The figure shows that the discontinuity closes largely because of improvement in the performance of "control" panchayats. This result is consistent with the earlier result that the ruling party is incrementally converting "control" panchayats into "treated" panchayats by recruiting opposition candidates. One interpretation is that the recruitment was not yet complete in 2014, but had largely been completed by 2016. The figure may suggest the ruling party has expanded the frontier of its power deeper into the opposition's strongholds.

The pattern is only suggestive—there is no way to test whether the discontinuity would have remained had the recruitment never happened. But this interpretation does offer a coherent explanation that reconciles the pattern in the figure with the results of the preceding sections.

8 Conclusion

In their seminal paper on party organization in Western democracies, Katz and Mair (1995) note that parties have become semi-state agencies: "[W]inning or losing may make less difference to a party's political objectives because of the absence of great policy battles, but could make a good deal of difference to its sheer survival, since the resources for its sustenance now come increasingly from the state." On India, Singh (1997) writes that "In the last few years the minority and coalition governments—at the centre and in the states—have used funds either to

[24] The results are similar if we add assembly constituency fixed-effects (Appendix B.3) or use the raw vote share (Appendix B.4).

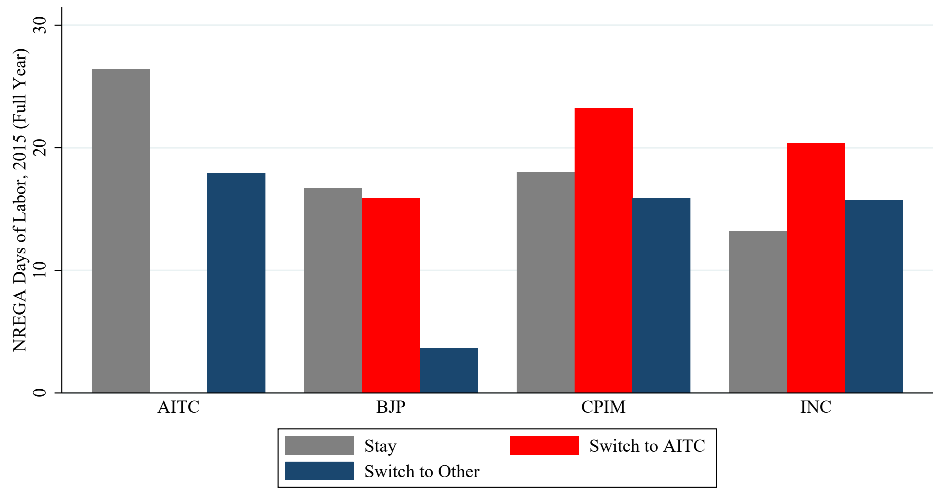
build patronage-based support networks or to bribe opposition MPs [Member of Parliament] at critical junctures." Our paper shows that government resources can play a key role in a political party's strategy to tighten and extend its grip on power across three tiers of government. This occurs because there are important complementarities of power between the tier of government that determines the allocation of resources and the tier of government that controls the program implementation.

Within India, West Bengal's local government institutions are unusual in the sense that politicians are explicitly members of a political party. Most other states require local politicians to run without party affiliations. While the party preferences of a candidate may be known or implied, this makes them unobservable for researchers and increases the difficulty of exploiting the complementarities of office for political parties. More generally, however, our study context is not atypical in developing countries. The AITC as a political party is primarily built as a vehicle for the political ambitions of its leader, which is a common feature among many political parties. And many countries and international organizations have pushed to decentralize power in recent years through transferring control over government program implementation to lower tiers of government.

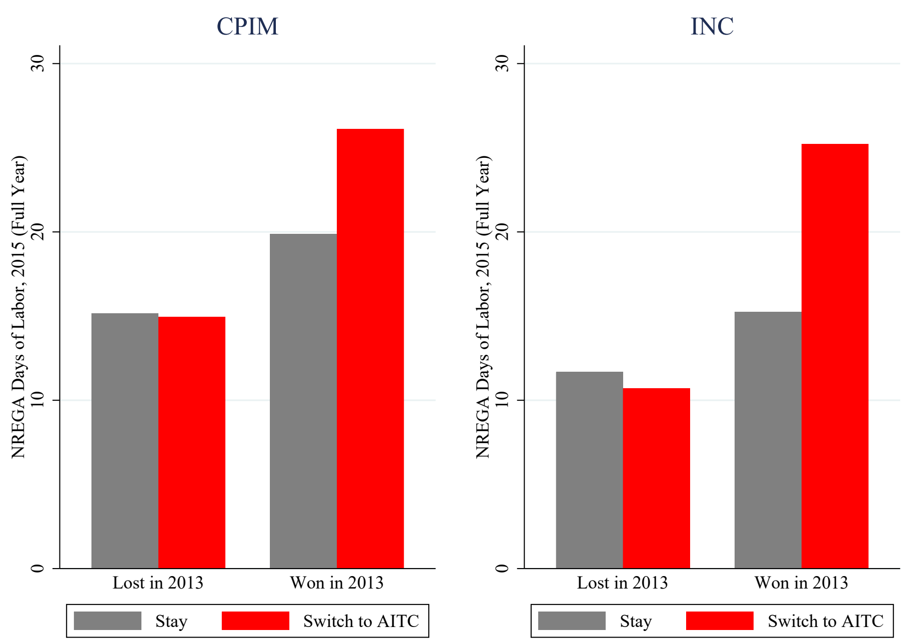
An interesting avenue for future research is to explore what happens once a party like the AITC loses power, and what conditions enable a change in government in this situation. Our proposed mechanism suggests that control over one office makes extending power to other positions easier, strengthening a party's position further. Reversing this development could require a miscalculation from the incumbent or a large enough external shock, as is often the case for authoritarian regimes. Potentially there are unexplored strategies that the political opposition could take to curb the process.

Figure 4
Payments Conditional on 2013-to-2018 Transition

a) Overall:



b) Winners vs. Losers, Main Opposition:



Note: Each bar shows the average 2015 NREGA allocation to candidates conditional on whether they "stay" with or "switch" from the party they were registered with in 2013 (which is labeled on the horizontal axis). For example, candidates who "stay" with the AITC get roughly 26 days of labor while those who "switch" get roughly 18 days. See Footnote 21 for the statistical significance of these differences.

Figure 5

Seats Gained Versus the Running Variable

Note: The left-hand panel restricts the sample to panchayats that lie within 0.6 of the cutoff for an absolute majority (based on the 1-norm). We divide the distance into bins of width 0.15 and calculate the average net gain of candidates for the AITC. The net gain is calculated as the number who switch from another party (or independent status) into the AITC minus the number who switch from the AITC. We average across panchayats within the bin. The blue dashed lines show the overall average on either side of the cutoff. The right-hand panel plots the regression discontinuity of the relative AITC vote share (share within the panchayat minus overall share in the constituency) for both the 2014 national election and the 2016 state election. We remove district and parliamentary constituency fixed effects to homogenize the two outcomes. For each year we restrict the sample to the optimal bandwidth (Calonico et al., 2014) and divide the running variable on either side of the cutoff into 12 equally spaced bins.

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A Online Appendix: Theoretical Arguments

A.1 Misaligned Incentives Reduce Political Targeting

A.1.1 $\alpha > 0$ and $\beta_k = 0$

Let θ be the Lagrange multiplier on the state politician's constraint (2), and μ_k the local politician's constraint (4). The state politician chooses B_k to satisfy

$$\theta = \frac{\partial W_k}{\partial B_k} + \alpha \frac{\partial V_k}{\partial B_k} \tag{14}$$
$$= \mu_k + \alpha \left[\sum_i v_i'(b_i^*) \frac{\partial b_i^*}{\partial B_k} \right] \tag{15}$$

where the second equality follows from the Envelope theorem. Define

$$g_i = \frac{\partial b_i^*}{\partial B_k}$$

Let I_k be the number of households in locale k and let $\bar{v}_i'$ and $\bar{g}_i$ denote the within-locale mean of v_i' and g_i. Simple algebra yields

$$\sum_i v_i' g_i = \sum_i (v_i' - \bar{v}_i')(g_i - \bar{g}_i) + \bar{v}_i' \bar{g}_i \tag{16}$$

Note that

$$\bar{g}_i = \frac{\sum_i \frac{\partial b_i^*}{\partial B_k}}{I_k} = \frac{1}{I_k}$$

where the second equality follows from differentiating both sides of (4) with respect to B_k.

Combining this expression with (16) and (15) yields

$$\theta = \mu_k(B_k, I_k) + \alpha \left[\sum_i (v_i' - \bar{v}_i')(g_i - \bar{g}_i) + \frac{\bar{v}_i'}{I_k} \right] \tag{17}$$
$$= \mu_k(B_k, I_k) + \alpha \left[I_k Cov\left(v_i', \frac{\partial b_i^*}{\partial B_k} \right) + \frac{\bar{v}_i'}{I_k} \right] \tag{18}$$

The extent to which (18) diverges from the welfare-maximizing allocation—the case where $\alpha = 0$ and the Lagrange multipliers are equalized—depends largely on the size of the covariance term.

This term captures the extent to which a marginal increase in B_k is distributed across households in a way that covaries with their marginal political importance. When v_i differs substantially from u_i, the covariance is small. In the limit where the covariance approaches zero and the number of households is large enough that $\bar{v}_i'/I_k \approx 0$ the first-order condition (18) converges to the condition characterizing a welfare-maximizing allocation with no political misallocation.

A.1.2 $\alpha = 0$ and $\beta_k > 0$

We sketch this argument in two steps. First we show that the state politician will allocate less funds to a local politician who engages in political targeting. Let $\hat{b}_i'(B_k;\beta_k)$ be the targeting function of the local politician. Given that $\alpha = 0$ the state politician chooses B_k to satisfy

$$\theta = \frac{\partial W_k}{\partial B_k} \tag{19}$$

$$= \sum_i u_i'(\hat{b}_i'(B_k;\beta_k))\hat{b}_i'(B_k;\beta_k) \tag{20}$$

$$= \sum_i \hat{b}_i'(B_k;\beta_k)\left[u_i'(\hat{b}_i'(B_k;\beta_k)) - \bar{u}_i'(B_k;\beta_k)\right] + \bar{u}_i'(B_k;\beta_k) \tag{21}$$

where $\bar{u}_i'(B_k;\beta_k)$ is the average marginal utility among households in k and the third line follows because $\sum_i \hat{b}_i'(B_k;\beta_k) = 1$ by the local politician's budget constraint. The first term is a measure of how well the local politician is directing each marginal dollar received to households with above-average marginal utility from benefits. If $\beta_k = 0$ this term is zero because the optimal allocation will equalize marginal utility across households. To the extent that the local politician targets benefits away from the neediest households, the term will be negative. As the first term becomes more negative the equality will hold only if the second term, the average marginal utility, becomes more positive. Since $\bar{u}_i'(B_k;\beta_k)$ is decreasing in B_k, a higher average marginal utility implies a lower level of B_k. In other words, the local politician's budget is cut as his targeting becomes more political.

The second step is to show that the local politician takes the state politician's behavior into account. The local politician's Lagrangian is

$$\mathscr{L} = \sum_i u_i(b_i) + \beta_k \sum_i v_i(b_i) + \mu_k \left[B_k\left(\{b_i\}\right) - \sum_i b_i \right] \tag{22}$$

where the crucial feature is that the local politician understands that B_k is a function of his targeting $\{b_i\}$. His optimal allocation will satisfy

$$u_i'(b_i) + \beta_k v_i'(b_i) = \mu_k \left[1 - \frac{\partial B_k}{\partial b_i}\right] \tag{23}$$

The term $\frac{\partial B_k}{\partial b_i}$ measures how much the state politician will increase or decrease the local politician's budget in response to a marginal increase in benefits targeted to i. The term will be negative if increasing benefits to i will reduce aggregate welfare, as it would if i is being targeted for its politician importance rather than its objective need. Now define the "efficiency weight" of i as

$$e_i = \frac{1}{1 - \frac{\partial B_k}{\partial b_i}} \tag{24}$$

This term is large when targeting benefits to i will increase total welfare and thus increase the number of projects received by k from the state politician. We can rewrite the local politician's first-order condition as

$$e_i \left[u_i'(b_i) + \beta_k v_i'(b_i)\right] = \mu_k \tag{25}$$

This condition shows that marginal utility from targeting i will be magnified if doing so increases total welfare, and diminished otherwise. In other words, the likely impact of targeting on the local politician's budget disciplines him from diverging too far from the choices that maximize household welfare.

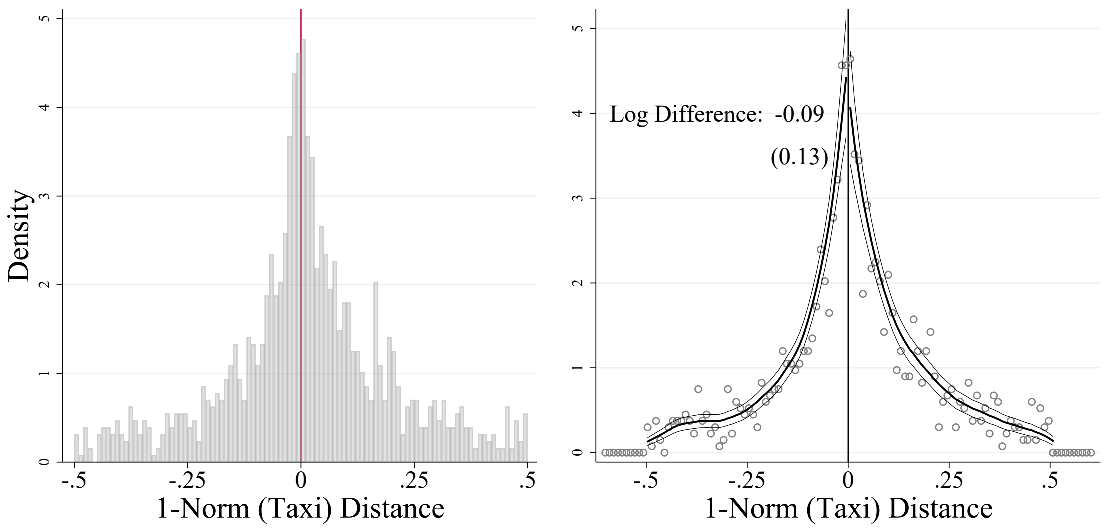
B Appendix: Additional Empirical Results

B.1 Tests for Manipulation

Figure B1 shows a McCrary test for whether there is a discontinuity in the density of the one-norm at the margin where the AITC wins an absolute majority (McCrary, 2008). Any such discon-

Figure B1

McCrary Density Test



tinuity would imply that the AITC or one of its competitors is able to manipulate the outcomes of elections to ensure it wins barely enough votes in barely enough seats to win a majority. Such precise manipulation is implausible because the Election Commission of India is a non-partisan bureau that is widely respected and considered free from corruption. Figure B1 confirms that there is no such discontinuity.

Tables B1—B3 report a number of balance tests by estimating Equation 9 on outcomes that were determined before the 2013 panchayat election (in mid-2013). Table B1 uses data from the 2011 Census to test for whether the AITC was systematically better at winning a narrow absolute majority in areas with particular characteristics than in others. Columns 1–4 of Table B1 show, however, that there is no evidence that the AITC was more likely to hold a narrow absolute majority in areas with a larger number of households, a higher population, or more lower-caste inhabitants (Scheduled Castes and Scheduled Tribes). Columns 5–8 find no evidence of a discontinuity in the availability of infrastructure (roads), schools of different types or the distance to an internet cafe. Table B2 runs a similar set of balance tests on election outcomes from the 2011 state and 2009 national election. We find no systematic difference in the vote share of any of the four major parties in either election. Table B3 tests for differences in aggregate job allocations prior to the 2013 local election. If the AITC were able to precisely manipulate the election

Table B1
Balance Tests: Census Outcomes

	(1) Households	(2) Population	(3) SC Pop	(4) ST Pop	(5) Road	(6) Primary Schools	(7) Private Schools	(8) Internet Cafe
RD Estimate	61.419	225.536	111.423	73.257	-0.000	0.285	-0.053	-0.001
	(129.376)	(542.426)	(331.370)	(185.139)	(0.020)	(0.568)	(0.095)	(0.013)
Obs in BW	1264	1299	1187	1231	1295	1305	1299	1214
Bandwidth	0.594	0.687	0.460	0.527	0.676	0.704	0.692	0.498
Robust p-val	0.583	0.582	0.660	0.762	0.988	0.649	0.543	0.819
Mean Left of Cutoff	3984.278	17821.926	5068.562	1246.921	0.148	16.674	0.529	0.065
Metric	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm

Note: "Robust p-val" gives the p-value after adjusting for bandwidth uncertainty (see Calonico et al., 2014). "Metric" gives the distance metric (to AITC absolute majority) used as the running variable. Bandwidths are MSE-optimal. "Mean Left of Cutoff" in Panel C gives the mean of the outcome for observations within one-tenth of the bandwidth on the left of the cutoff. Standard errors are calculated using 3 nearest neighbors. See text for description of each specification. Outcome data comes from the 2011 Indian Census.
*p=0.10 **p=0.05 ***p=0.01

share by targeting resources, we might expect significant imbalance on pre-election job allocations. We test for differences in the 2013 and 2012 allocations during the dry season (the first three months of the year). We also shift back the calendar date of the 2014 national election to 2013 and 2012 to test for differences in the 4 weeks before that election (both periods were before the 2013 local election). We find no significant differences. These three tables of balance tests further support the internal validity of the multi-dimensional RD design.

Table B2
Balance Tests: Prior Elections

	2009 National Election				2011 State Election			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AITC	BJP	CPM	INC	AITC	BJP	CPM	INC
RD Estimate	0.000	-0.005	-0.004	0.010	0.018	-0.002	0.002	0.012
	(0.019)	(0.005)	(0.018)	(0.015)	(0.014)	(0.003)	(0.017)	(0.011)
Obs in BW	1211	1219	1240	1231	1211	1151	1286	1166
Bandwidth	0.470	0.477	0.508	0.495	0.467	0.380	0.597	0.402
Robust p-val	0.925	0.456	0.787	0.510	0.305	0.646	0.973	0.268
Mean Left of Cutoff	0.362	0.054	0.317	0.089	0.425	0.040	0.314	0.029
Metric	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm	1-Norm

Note: "Robust p-val" gives the p-value after adjusting for bandwidth uncertainty (see Calonico et al., 2014). "Metric" gives the distance metric (to AITC absolute majority) used as the running variable. Bandwidths are MSE-optimal. "Mean Left of Cutoff" in Panel C gives the mean of the outcome for observations within one-tenth of the bandwidth on the left of the cutoff. Standard errors are calculated using 3 nearest neighbors. See text for description of each specification. Outcome data comes from aggregating polling-station-level data from the 2009 and 2011 elections to the panchayat-level and calculating the vote share for the given party. (AITC=All-India Trinimool Congress, BJP=Bharatya Janata Party, CPM=Communist Party-Marxist, INC=Indian National Congress)
*p=0.10 **p=0.05 ***p=0.01

Table B3
Balance Tests: Pre-2013 Election Job Allocations

	(1)	(2)	(3)	(4)
	Dry Season 2013	4 Week Pre-Poll 2013	Dry Season 2012	4 Week Pre-Poll 2012
RD Estimate	0.422	-0.357	0.213	-0.152
	(0.918)	(0.299)	(1.005)	(0.478)
Obs in BW	1072	1113	1187	1125
Bandwidth	0.397	0.463	0.633	0.484
Robust p-val	0.783	0.192	0.878	0.700
Mean Left of Cutoff	6.286	1.034	7.216	2.266
Metric	1-Norm	1-Norm	1-Norm	1-Norm

Note: "Robust p-val" gives the p-value after adjusting for bandwidth uncertainty (see Calonico et al., 2014). "Metric" gives the distance metric (to AITC absolute majority) used as the running variable. Bandwidths are MSE-optimal. "Mean Left of Cutoff" in Panel C gives the mean of the outcome for observations within one-tenth of the bandwidth on the left of the cutoff. Standard errors are calculated using 3 nearest neighbors. See text for description of each specification. Outcome data comes from 2013 and 2012 election data. "4 Week Pre-Poll" refers to the 4 weeks prior to the calendar date of the 2014 election shifted back to 2013 and 2012.
*p=0.10 **p=0.05 ***p=0.01

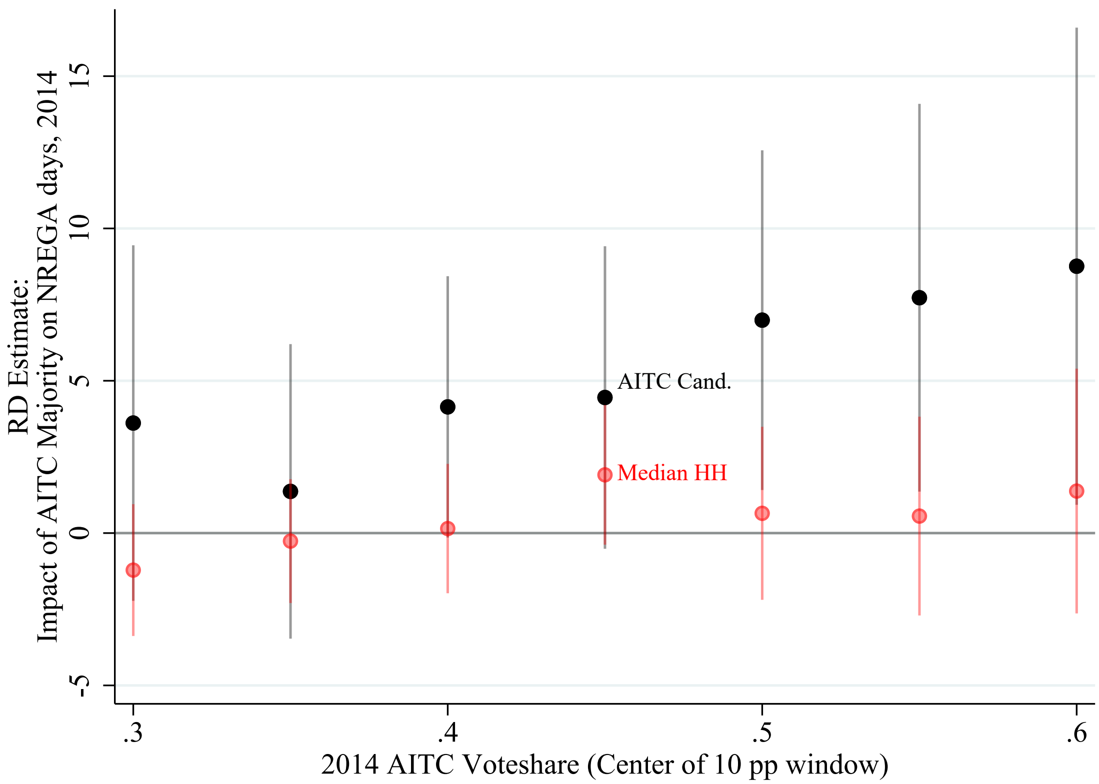
B.2 AITC Candidates are not Just Proxying for AITC Supporters (Table 5)

An alternative interpretation of Table 5 is that AITC candidates get no specifical treatment. Candidacy is just a proxy for being an AITC supporter, and all AITC supporters get larger payments than non-supporters.

To test this hypothesis we calculate the payment made to the *median* household within each village and test for how the median household's payment changes when the AITC takes control. We calculate how this RD estimate changes *as a function of the AITC's 2014 vote share*. As the AITC's village-level vote share approaches and exceeds 50 percent, we would expect the median household to be an AITC supporter (because at least half of all villagers voted for the party). If the alternative interpretation is true—that is, if AITC candidates are just readily identifiable AITC supporters—we would expect the size of the RD estimates for the median household to converge to the size for AITC candidates from the same village.

We run this test and plot the results in Figure B2. For each test we choose a vote share $(0.3, 0.35, \ldots 0.6)$ and restrict to villages where the 2014 AITC vote share was ± 0.1 of the center point. We use the number of days of labor throughout the full year of 2014 for this test because the difference in Table 5 is largest for the full-year outcome, and thus the pattern of convergence ought to be the most stark. The figure shows no evidence that the RD estimates for the median household are converging to those of the AITC candidates, even when the village-level vote share is in the range 50—70 percent (the estimate furthest to the right).

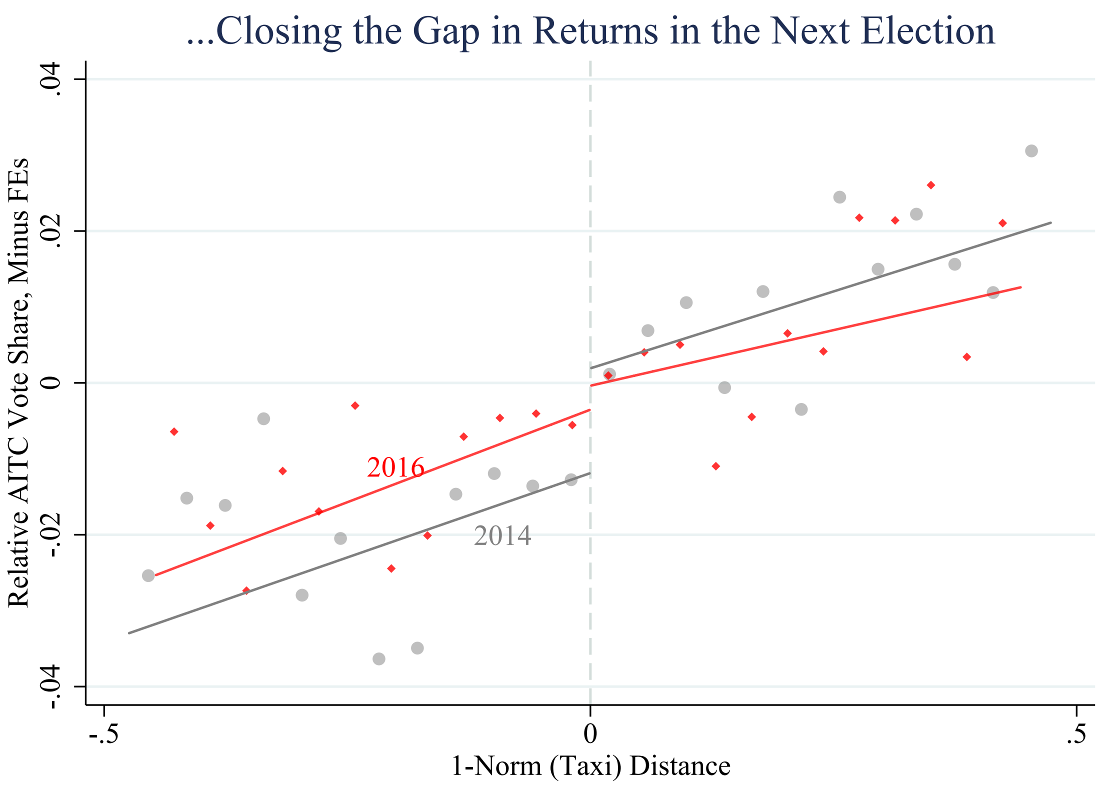
Figure B2



Note: For each test we choose a vote share $(0.3, 0.35, \ldots 0.6)$ and restrict to villages where the 2014 AITC vote share was ± 0.1 of the center point. The outcome is the NREGA job allocation throughout the full year of 2014. We plot the RD impact on the median job allocation and the job allocation for AITC candidates within those villages. All estimates use the Calonico et al. (2014) method to estimate the bandwidth and include district and constituency fixed-effects (see Section 4.3). The standard errors are clustered by panchayat.

B.3 Right-Hand Panel of Figure 5 Using Assembly Constituency Fixed-Effects

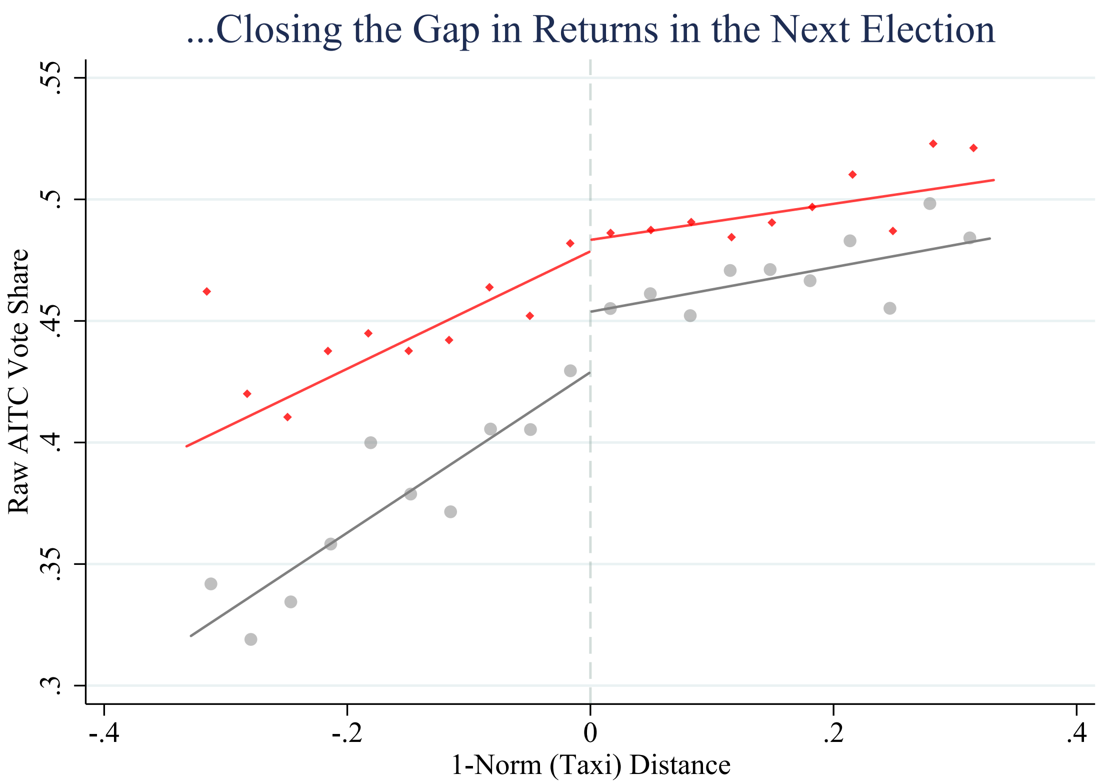
Figure B3
The Contrast Between 2014 and 2016 is Equally Stark Using Assembly Constituency Fixed-Effects



Note: This figure is exactly the same as the right-hand panel of Figure 5 except vote leans in both years are stripped of assembly constituency fixed-effects rather than parliamentary constituency fixed-effects.

B.4 Right-Hand Panel of Figure 5 Using Raw Vote Shares

Figure B4
The Contrast Between 2014 and 2016 is Equally Stark Using Raw Vote Shares



Note: This figure is exactly the same as the right-hand panel of Figure 5 except it uses raw vote share as the outcome and does not strip out district and constituency fixed-effects.

B.5 Are Close Elections Unusual, and How Might the NATE Differ from the LATE?

While a close election design achieves causal inference, it does so only within a set of closely divided elections. This Neighborhood Average Treatment Effect (NATE) may not be informative about the average treatment effect if close elections occur in a relatively small and unusual set of places. A party might use its power differently in a highly contested battleground than in a stronghold.

To some degree this problem is less salient for our mutlidimensional design because a more diverse set of outcomes will appear near the cutoff. A directly elected council president who barely won is clearly insecure. But a multi-constituency local council where the AITC barely won a majority could comprise only closely won constituencies, or it could comprise dozens of stronghold constituencies alongside one or two pivotal swing constituencies.

That may explain why the majority of panchayats are close to the cutoff. The bars in Figure B5 show the share of our sample that lies within a widening set of windows around the cutoff (as measured with the one-norm). Even a very narrow window of 0.05, meaning the absolute majority was won or lost by a cumulative total of only 5 percentage points, accounts for nearly 25 percent of the sample. A window of 0.3 contains over half of the sample. For comparison the optimal bandwidth of the baseline specification in Table 1 is 0.775, implying our main estimates are based on well over half the sample.

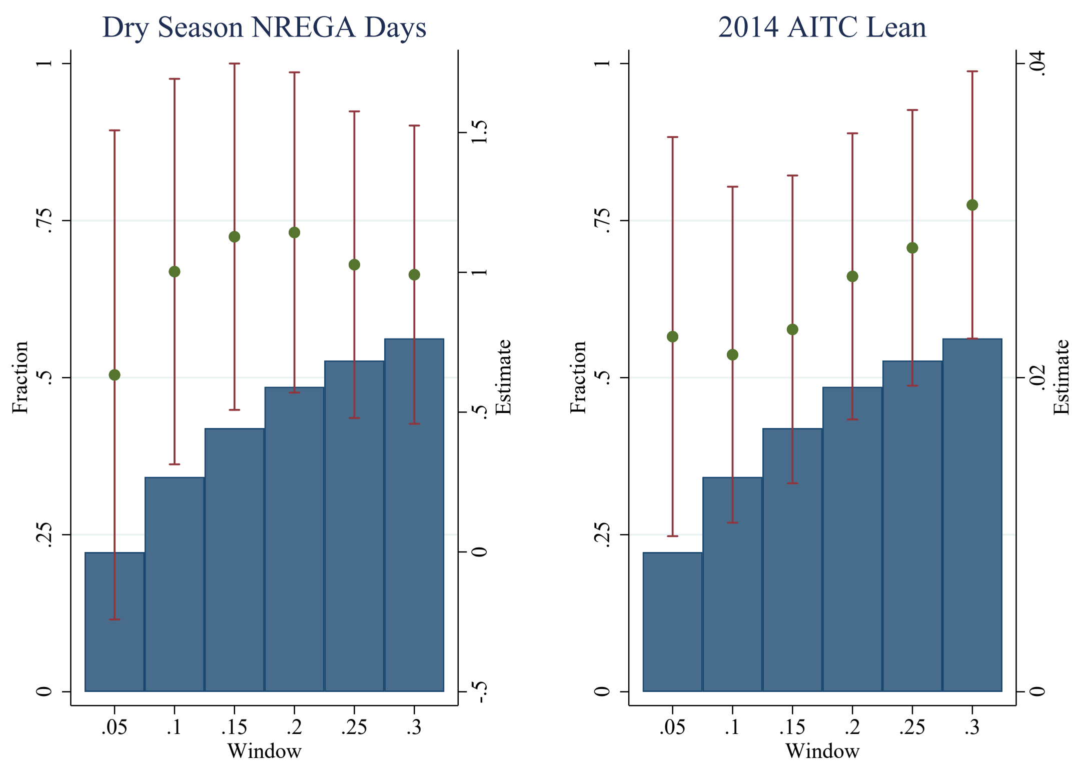
Though the RD estimate is weighted disproportionately towards the very closest elections, Figure B5 also shows that even a simple comparison of means between AITC and non-AITC panchayats yields similar estimates. We restrict to observations within the window and run a simple ordinary least squares regression of the outcome on a dummy for whether the AITC holds an absolute majority. The left-hand panel shows estimates when the outcome is the number of dry season NREGA days from 2014 to 2016. The estimates show no obvious pattern as the window widens. All lie within each other's 95 percent confidence intervals, and within the 95 percent confidence interval of the RD estimate. At the widest window of 0.3 the estimate is nearly identical to the RD estimate. The right-hand panel shows a more pronounced positive relationship between the size of the window and the estimate for the 2014 election return, but that is to be expected for a political outcome. Places that elected (rejected) an AITC majority in 2013 by a wider margin will also likely vote for the AITC by a wider (narrower) margin in 2014. Taken together these results are not consistent with the fear that areas right at the cutoff are dramatically different from those within 0.3 of the cutoff. Though this window may seem narrow, it accounts for most of the sample.

We can also test more directly whether there are major differences between areas decided by close versus non-close elections. Using the full sample, we estimate a simple OLS regression of several outcomes on a dummy for whether the running variable is "close" to the cutoff (meaning the outcome of the 2013 election lies within a range of 0.05 based on the one-norm metric). Table B4 shows the estimates from such regressions on panchayat-level outcomes from the 2011 census, and Table B5 for dry season NREGA labor for several years. Table B4 suggests close elections may occur in places that are slightly further from roads, but otherwise there is no difference of statistical or economic significance. Table B5 suggests closely decided panchayats may receive slightly smaller NREGA allocations, but the result is at best marginally significant in one year.

These results cannot prove that randomly assigning non-close areas to AITC control would have impacts similar to those estimated by the RD. But they also do not give obvious reason to expect the NATE is highly unrepresentative.

Figure B5

Share of Observations and Differences in Outcomes Between AITC and non-AITC Panchayats as the Window around the Cutoff Widens



Note:

Table B4
Close Elections vs. Non-Close Elections: Census Outcomes

	(1) Households	(2) Population	(3) SC Pop	(4) ST Pop	(5) Road	(6) Primary Schools	(7) Private Schools	(8) Internet Cafe
Close GP	-44.465	-216.295	17.246	-71.002	-0.031**	0.390	-0.076	-0.009
	(87.782)	(379.533)	(210.839)	(116.401)	(0.013)	(0.413)	(0.065)	(0.008)
N	1852	1852	1852	1852	1848	1852	1852	1848
Mean Outcome	4080.553	18210.514	4984.143	1344.313	0.172	16.885	0.534	0.076

Note: We estimate a simple OLS regression of the outcome on a dummy for whether the running variable is "close" to the cutoff (meaning the outcome of the 2013 election lies within a range of 0.05 based on the one-norm metric). Outcome data comes from the 2011 Indian Census. "Road" refers to the share of villages within the panchayat that are connected by a "major district road." The columns that mention schools use as the outcome the number of that type of school in the panchayat. "Internet Cafe" is the share of villages with an internet cafe.
*p=0.10 **p=0.05 ***p=0.01

Table B5
Close Elections vs. Non-Close Elections: Dry Season NREGA Days of Labor

	(1) 2012	(2) 2013	(3) 2014	(4) 2015
Close GP	-0.548*	-0.049	-0.560	0.030
	(0.301)	(0.263)	(0.389)	(0.230)
N	1959	1959	1959	1959
Mean Outcome	7.919	5.753	11.560	2.949

Note: We estimate a simple OLS regression of the outcome on a dummy for whether the running variable is "close" to the cutoff (meaning the outcome of the 2013 election lies within a range of 0.05 based on the one-norm metric). The outcome in each column is the average per-household NREGA allocation during the dry season of that year.
*p=0.10 **p=0.05 ***p=0.01

B.6 Is the Sample of Candidates who Ran Again in 2018 Unusual?

Section 7 infers party-switching using a sample of 2013 local candidates who ran again in the 2018 local election. One concern is that this sample is selected in ways that might produce misleading results. This appendix studies how the sample differs from the full set of candidates. We restrict to the subset who were registered in 2013 with one of the four major parties: the AITC, the BJP, the CPIM, and the INC. Within this subset roughly 8 percent are in the sample used in Section 7.

Table B6 shows estimates from regressions of a dummy for inclusion in the sample on several political characteristics of the candidate. Candidates who won their election and received a higher share of votes in 2013 are more likely to be in the sample. That is not surprising, as unsuccessful candidates have lower chances of success in the next election. Constituencies that were contested and with more candidates are also more likely to feature repeat candidates. The incumbency advantage of a winner is likely more valuable in a contested seat, as these are less likely to be safe party strongholds. After controlling for the success of the candidate, AITC candidates are less likely to run for re-election (compared to the BJP, the excluded category in the regression). That may be because these candidates are more likely to seek higher office, or because the ruling party's brand and political machine makes it less reliant on incumbency effects. Candidates from the opposition parties are even less likely to field repeat candidates, perhaps because holding office is less valuable when they control so few local councils.

These patterns by themselves are not necessarily a problem for our analysis. Since we argue that the AITC seeks recruits to gain majorities on councils where it didn't win enough seats, it helps our argument that the sample is mostly candidates who actually won in 2013.

What could potentially be problematic is the selection by party, as much of our analysis studies whether average payments differ by party. It would be a problem if, for example, the AITC candidates who don't run for re-election are paid systematically less than the ones who do. We can test directly for this pattern by regressing 2015 NREGA days of labor on the dummy for whether the candidate is in the sample, and its interaction with the party dummies.

Columns 1 and 2 of Table B7 show that although candidates in the sample get more days of labor than those that are not, the effect vanishes after we control for whether the candidate wins

Table B6

Correlates of Being in the Sample of Candidates Who Run in 2018

	In Sample			
	(1)	(2)	(3)	(4)
Winner	0.080***	0.070***	0.066***	0.063***
	(0.002)	(0.003)	(0.003)	(0.003)
Vote Share		0.031***	0.057***	0.071***
		(0.005)	(0.006)	(0.007)
Numer of Candidates			0.008***	0.007***
			(0.001)	(0.001)
Contested Election			0.002	0.018***
			(0.006)	(0.007)
AITC				-0.008**
				(0.004)
CPIM				-0.031***
				(0.004)
INC				-0.017***
				(0.003)
N	84082	84079	84079	84079

Note: We estimate a simple candidate-level OLS regression of a dummy for whether the candidate is in the sample used for Section 7. We restrict to the subset of candidates from one of the four major parties. The BJP is the excluded category (among the four party dummies). We cluster standard errors by race.
*p=0.10 **p=0.05 ***p=0.01

Table B7

Candidates in the 2013-2018 Sample Are Not Unusual in their 2015 NREGA payments

	2015 NREGA Days		
	(1)	(2)	(3)
In Sample	2.177***	-0.440	-2.023
	(0.707)	(0.701)	(2.234)
Winner		9.861***	8.820***
		(0.368)	(0.382)
AITC			3.390***
			(0.684)
CPIM			-1.133*
			(0.686)
INC			-0.902
			(0.726)
In Sample × AITC			1.605
			(2.436)
In Sample × CPIM			1.620
			(2.621)
In Sample × INC			0.568
			(2.775)
N	27715	27715	27715
P-val on In-Sample Vars			0.365

Note: We estimate a simple candidate-level OLS regression of days of NREGA labor in 2015 on several predictors including a dummy for whether the candidate is included in the sample used in Section 7. We restrict to the subset of candidates from one of the four major parties. The BJP is the excluded category (among the four party dummies). We cluster standard errors by race. The row "P-val on In-Sample Vars" shows the p-value from an F-test on the joint significance of "In Sample" and the terms interacted with it. *p=0.10 **p=0.05 ***p=0.01

their election. Column 3 shows that the interactions between the dummy for being in the sample and the dummies for party affiliation are not significant. An F-test for the joint significance of the main effect and the interactions cannot reject the null that all are zero. This suggests there is no systematic difference in payments to candidates in the sample, regardless of the 2013 party of the candidate.

C Data Appendix

C.1 Raw Sources of Data

We rely most heavily on 3 datasets that we constructed by converting unstructured administrative data into structured data files. As described in later sections, we supplement these data with several other sources that were scraped, digitized, or obtained directly from government officials.

The most important original dataset is the NREGA job card dataset, which was scraped in late 2018 through early 2019 from the government's public web portal (https://nrega.nic.in). Figure B6 shows an example of a job card (the names and identification numbers have been replaced in this figure to protect the identity of the household). The parts of the record we use are the job card details, the family details, and the employment given.

We also scrape outcomes of the 2013 and 2018 gram panchayat elections from the website of the State Election Commission of West Bengal (http://www.wbsec.gov.in). Figure B7 shows an example of the results for a single panchayat. Some panchayats did not report results through this portal and are excluded from our study.

Our third major source of data is the official "Form 20" tally sheet of booth-level vote counts for each parliamentary constituency and assembly constituency, drawn from the website of the Chief Election Officer of West Bengal (http://ceowestbengal.nic.in/). Figure B8 shows an example of a tally sheet from the 2014 national election. We hired a contractor to apply optimal character recognition to convert these results to structured data, and validated the totals using basic consistency checks. The Form 20 sheets for the 2016 state election were too blurry to be read by machine. Instead we hired four contractors to manually enter the data, which was then validated and corrected by an undergraduate research assistant.

C.2 Constructing the Dataset Used to Show the Impact of AITC Control on National and State Election Outcomes

We construct 3 distance metrics to the frontier of an AITC absolute majority using the 2013 gram panchayat election outcomes. These panchayat-level distance metrics are the running variable for the regression discontinuity design. The next step is to merge the running variable to panchayat-level aggregates of the vote count in the 2014 and 2016 elections.

As we were unable to find any record specifying which gram panchayat contained each polling station, we constructed our own crosswalk through the NREGA job card data. Some fraction of households registered for their job cards using their election photo ID card (EPIC). As shown in Figure B6, those households have the EPIC number listed on the job card. We constructed a random sample of 10 epic numbers from each village in each gram panchayat and queried those numbers against an online portal created by the Chief Election Officer of West Bengal to let voters find their polling station for the 2019 election (which, at this stage of the data construction, was in progress). Since most locations used for polling in 2014 were retained for 2019, this dataset gave us a mapping between job card numbers and the names of buildings used by the job card holder. We assigned a polling location to a gram panchayat if the plurality of job cards linked to EPICs registered to vote at that location were also registered under the gram panchayat.[25] This gave us a crosswalk between the names of gram panchayats and the names of polling locations.

Since the Form 20 tally sheets record only the numerical ID of a polling station, we had to link the station-level vote counts by ID number to the data constructed by Susewind (2016), which contains the ID number and name of each 2014 polling booth. We cleaned these names and consolidated the data to the building-level.[26] We fuzzy-matched this dataset by the name of the polling location to the crosswalk constructed above, and hired two native Bengali speakers to independently validate the matches. We matched 2016 names back to 2014 stations based on their numerical identifiers.[27]

[25] In the vast majority of cases all EPICs registered to vote at a polling station were linked to a job card from the same panchayat.

[26] Some polling stations are actually separate rooms within the same building. Since the crosswalk between panchayats and 2019 stations gives only the polling location, we consolidated 2014 and 2016 vote counts within building.

[27] We have found no publicly available official correspondence between 2014 and 2016 stations, nor any description of how station identifiers were assigned. But based on a limited subset of assembly constituencies where we observe the names of the 2016 stations, and on information recovered from old versions of the West Bengal CEO website found on the Internet Archive, we have deduced that in the vast majority of cases a 2014 station reused in 2016 will retain the same ID. In the vast majority of cases, new stations were given names that contain letters or slashes to avoid having to renumber existing stations. Staff affiliated with the Election Commission of India has confirmed that this is the standard practice followed in recent elections. We estimate that this rule

C.3 Constructing the Dataset Used to Show the Impact of AITC Control on NREGA Allocations

We restrict our sample of job cards to the subset living in panchayats linked to polling stations (see previous section). Using the station to panchayat crosswalk we infer the polling date of each panchayat, which lets us calculate the the number of days of labor received by each job card within the period 4 weeks after the date of polling as well as during the dry season (which we define as the first 12 weeks of the calendar year) and each full calendar year. To be precise, we record a job card as having received some number of jobs within a period if it was given a job spell whose start date fell within the period. If a job card did not have a job spell within that period, it was recorded as receiving zero days of labor.

We identify the subset of these job cards that are AITC candidates by fuzzy string-matching candidates by name to the full set of NREGA recipients (individuals registered under any job card). We discard cases where the gender or caste group of the recipient is inconsistent with the reservation status of the district being contested by the candidate (which would imply the match is incorrect). We also discard any cases where multiple candidates or NREGA recipients have the same name (as they are functionally indistinguishable). This set of machine-identified matches was then hand verified by two native Bengali speakers working independently, and cases where the two disagreed were adjudicated by the authors. We tag a jobcard as matched to an AITC candidate if any individual registered under the job card was matched. After discarding ambiguous cases, in the full sample we match just over half of AITC candidates to a job card.

We calculated the mean days received by all job cards within the panchayat (our measure of

held in 95% of assembly constituencies. In the remainder, a few stations are added to the middle of the list and subsequent stations are renumbered accordingly. But even in these cases, we estimate (using the cases where we know the names of 2014 and 2016 stations) that we only assign the 2016 polling station to the wrong panchayat 30% of the time. This is because numerically adjacent stations are generally in the same panchayat, minimizing the impact of the kind of transposition error caused by an insertion and renumbering. Taken together, these estimates imply that in 95 to 97% of cases the 2016 station is assigned to the correct panchayat. We confirm that when we use our matching approach, there is a strong correlation (R-squared of 0.9) between total valid votes cast in 2014 and 2016. We have also verified that Figure 5 is unchanged when we restrict the sample to the ACs that do not appear to have been renumbered. Finally, there is a small number of polling locations created for the 2016 election that were not used in the 2014 election. These stations necessarily were lost because we could not identify their names. The number of new stations was small enough—typically a handful in each assembly constituency—that the resulting measurement error is small. Most importantly, there is no reason to expect the resulting measurement error to change at the discontinuity.

"aggregate" allocations) as well as by the subset of job cards matched to an AITC candidate and the subset of individuals not recorded as AITC candidates. Though it is possible that some candidates are missed or mismatched, there is no reason to expect the level or sign of the resulting measurement error to systematically change at the discontinuity.

We calculate most of the average allocations within demographic group using data recorded on the NREGA job card. The one exception is "Muslim" versus "Non-Muslim," which we identify probabilistically using the names of the head of household and the head's closest male relative. For each job card we construct a list of name tokens (e.g. "Ajay Manohar Shenoy" comprises tokens "Ajay," "Manohar," and "Shenoy"). We use the listing sheets from the West Bengal subset of the 2006 Rural Economic Development Survey to create a large sample of tokens where the individual's religion is known. For each token we calculate the share of individuals in REDS that are Muslim and the share that are non-Muslim. We then estimate a person-level linear probability model based on whether any of the name tokens in the person's name are "positive for being Muslim," meaning at least 80 percent of people with that name token are Muslim, or "negative for being Muslim," which is the converse set. If the predicted probability of "Muslim" is greater than 50 percent, we predict the individual is Muslim. This person-level predictive model, when applied to a hold-out sample in REDS, is highly accurate. Within the set predicted to be Muslim, 98.7 percent are in fact Muslim. Within the set predicted not to be Muslim 94.8 percent are in fact non-Muslim. We then bring the token-level Muslim shares and the predictive procedure into the NREGA job card data to predict whether the job card holder is Muslim (based on whether the head of household's name is predicted to be Muslim).

C.4 Constructing the Village-level Datasets Used to Show Within-Panchayat Outcomes

All within-panchayat analyses use a village-level dataset constructed analogously to the two panchayat-level datasets above. We match polling stations to villages using the same method, and identify AITC candidates within each village using the same job card-level matches. The one new variable is the 2009 and 2011 average vote share within the village. We digitize station-level data from the Chief Election Officer, and merge the counts to station names scraped from an archived version of the website. We consolidate station-level data to the building-level using a similar method as described above for 2014 stations before fuzzy string-matching to 2014 locations by name (as above, the machine-generated matches are validated by two independent India-based research assistants). Since there is a nontrivial number of stations that do not match (and unlike the 2014 and 2016 vote counts, the 2009 and 2011 vote shares are used on the right-hand side of the regression) we average party-level vote shares within village rather than summing vote counts and subsequently calculating shares. This procedure reduces the risk of putting undue weight on one or two large stations, though in practice the results are almost identical to using the other method.

C.5 Constructing the Datasets On Party-Switching

We constructed the candidate-level dataset by fuzzy string-matching candidates by name and panchayat from the 2013 data to the 2018 data. We discard matches where the gender and caste of the 2018 candidate is inconsistent with the reservation status of the 2013 candidate.[28] We discard matches with a low match probability (below 98.95 percent) or cases where multiple candidates are matched. The final sample includes only candidates who appear in 2013 and are matched to 2018. We machine-match this subset of candidates by name to the job card data using a similar procedure to that outlined above.[29] We calculate the total labor allocation to the job card of each matched candidate for each year (restricting the sample only to those who did match to a job card). The final dataset is at the candidate-level (which we combine with the aggregate-level datasets by panchayat).

28 Unfortunately we do not know the actual gender and caste of the candidate in the 2013 data, only the reservation status of the seat being contested.

29 For this phase we did not hire native speakers to hand-validate the matches, as we noted that the additional step made almost no difference when applied to the AITC candidates. Nevertheless, for this phase we use only machine-matched candidates (even though we have hand validated matches for the AITC candidates) to ensure there is no systematic measurement error based on political party.

Figure B6

Sample Job Card
(Names and ID Numbers Changed to Protect Privacy)

Job card

MAHATMA GANDHI NATIONAL RURAL EMPLOYMENT GUARANTEE ACT

Job card No.:	WB-01-002-011-999/111	Family Id:	111
Name of Head of Household:	AJAY SHENOY		
Name of Father/Husband:	MANOHAR SHENOY		
Category:	OTH		
Date of Registration:	1/2/2008		
Address:			
Villages:	MAHATPUR-3		
Panchayat:	MAHATPUR		
Block:	CHAPRA		
District:	NADIA(WEST BENGAL)		
Whether BPL Family:	YES	BPL Family No.:	987654-IN50
Epic No.:	WB/12/079/123456		

Details of the Applicants of the household willing

S.No	Name of Applicant	Gender	Age	Bank/Postoffice
1	AJAY SHENOY	Male	35	Pukhuria - Tilakpur S.K.U.S. LTD
2	AJITA SHENOY	Female	68	Pukhuria - Tilakpur S.K.U.S. LTD

Signature/Thumb impression of Applicant　　　　Seal & Signature of Registering Authority

Period and Work on which Employment Given

S.No	Name of Applicant	Month & Date from which employment requested	No of Days	Work Name	MSR No.	Total Amount of Work Done	Payment Due
1	AJAY SHENOY	16/01/2008	6	Imp of road from H/O Abdul hamid sk to H/O Chandu Molla	2865	450	0
	Sub Total FY 0708		6			450	0
2	AJITA SHENOY	05/03/2009	6	Earthen Rood From the H/O Asan Ali Sk.to Modhu Molla	39626	484	0
3	AJAY SHENOY	05/03/2009	6	Earthen Rood From the H/O Asan Ali Sk.to Modhu Molla	39635	480	0
	Sub Total FY 0809		12			964	0
4	AJITA SHENOY	07/12/2009	6	Re-excavation of Khal the Plot of Alip Molla	45804	480	0
5	AJITA SHENOY	19/01/2010	6	Implimentation of earthen road from Masjid to Beledov	51865	588	0
	Sub Total FY 0910		12			1068	0
6	AJITA SHENOY	04/06/2010	5	Implimentation of earthen road cum bundh from ferryghat to fataghat	74273	450	0
7	AJITA SHENOY	09/06/2010	2	Desilting of Pond of Bidar Shaikh	74017	160	0
8	AJITA SHENOY	24/06/2010	2	Earthen road from Pakurtala to Primary school	78428	166	0
	Sub Total FY 1011		9			776	0
9	AJITA SHENOY	29/12/2011	5	Earth work in Bundh from Pukhuria fataghat to Paschimpara Snanerghat	83995	450	0
	Sub Total FY 1112		5			450	0

Figure B7
Example of 2013 Gram Panchayat Election Report

Gram Panchayat Election Results,2013

Zilla Parishad Name: Bankura
Panchayat Samity Name: BANKURA-I
Gram Panchayat Name: ANDHARTHOLE

Seat Name	Total Electors	Votes Polled	Votes Rejected	OSN	Candidate Name	Party Name	Votes Secured
I/1 WOMAN	1250	1019	106	1	MAMANI ROY	CPIM	352
				2	MALA ROY	BJP	78
				3	SARASWATI ROY	AITC	483
II/2 GENERAL	650	579	12	1	ARUP SHIT	AITC	273
				2	PARESH NANDI	BJP	17
				3	ROHIT SHIT	CPIM	277
III/3 SC WOMAN	893	745	42	1	JABARANI MANDAL	AITC	365
				2	BHABANI MONDAL	INC	122
				3	MINATI MANDAL	CPIM	200
				4	SHILA MONDAL	BJP	16
IV/4 SC	1029	845	40	1	ANADI MONDAL	AITC	334
				2	PIJUSH MANDAL	INC	163
				3	BUDDHADEB MONDAL	AIFB	270
				4	SUDHIR MONDAL	BJP	38
V/5 WOMAN	861	774	33	1	APARNA PATRA	CPIM	369
				2	BANALATA MUKHUTI	AITC	372
VI/6 SC WOMAN	1114	939	15	1	PARUL PARAMANIK	AITC	575
				2	PRATIMA MAL	CPIM	349
VII/7 GENERAL	868	713	64	1	ALAM RAFIKUL KHAN	INC	8

Figure B8

Example of 2013 Gram Panchayat Election Report

FORM 20

FINAL RESULT SHEET, PGE 2014

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PART-I

Total No. of Electors in Assembly Constituency : **216911**

Name of the Assembly Constituency : ***2, MATHABHANGA(SC)***

Sl. No.	Polling Station No.	No. of valid votes cast in favour of												Total of valid votes	No. of rejected votes	NOTA	No. of Test Votes	Total	No. of tendered votes
		Keshab Chandra Ray	Girindra Nath Barman	Dipak Kumar Roy	Renuka Sinha	Hem Chandra Barman	Kamal Krishna Bairagi	Dalendra Nath Ray	Nripen Karjee	Pijush Barman	Hare krishna Sarkar	Bangshi Badan Barman	Hitendra Das						
1	1	17	4	236	255	136	4	0	2	3	7	2	5	**671**	0	11	0	**682**	0
2	2	23	10	259	255	44	6	4	2	1	5	7	7	**623**	0	12	0	**635**	0
3	3	8	12	254	258	64	3	0	2	1	1	2	2	**607**	0	7	0	**614**	0
4	4	6	8	195	222	93	30	1	1	2	3	0	1	**562**	0	3	0	**565**	0
5	5	19	7	180	208	62	2	0	3	0	1	0	2	**484**	0	2	0	**486**	0
6	6	24	18	305	258	88	7	3	3	2	5	10	6	**729**	0	10	0	**739**	0
7	7	22	14	334	273	52	7	2	0	2	4	5	5	**720**	0	6	0	**726**	0
8	8	45	18	375	361	95	4	4	3	3	7	4	4	**923**	0	7	0	**930**	0
9	9	4	12	249	155	65	4	0	2	0	1	3	1	**496**	0	1	0	**497**	0
10	10	19	14	373	334	54	4	3	1	4	4	5	2	**817**	0	8	0	**825**	0
11	11	4	9	407	327	20	2	2	1	1	4	3	4	**784**	0	3	0	**787**	0
12	12	13	6	382	314	23	3	1	1	1	4	6	6	**760**	0	10	0	**770**	0
13	13	25	16	633	353	51	5	6	2	3	6	3	6	**1109**	0	12	0	**1121**	0
14	14	4	5	367	217	33	3	4	1	0	1	1	1	**637**	0	5	0	**642**	0
15	15	17	9	344	490	73	5	1	2	2	3	4	8	**958**	0	6	0	**964**	0
16	16	11	8	406	313	88	10	2	2	2	3	4	8	**857**	0	11	0	**868**	0