ESSAYS ON LOCAL GOVERNANCE IN INDIA

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ABSTRACT

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This dissertation studies local governments and the effects of their vertical and horizontal structures on public goods provision in India. The first chapter focuses on political representation and the vertical structure of decentralized governments. Political decentralization combined with minority representation has been purported to give power to the poor. Yet, it is unclear what form of minority representation can best achieve this. In this paper, I ask whether group (mis)alignment across local and intermediate level representations affect public goods distribution to the poor in the context of the Indian National Rural Employment Generation Scheme (NREGS), one of the world's largest social welfare program. Exploiting changes in caste representation driven by India's reservation system intended to increase minority caste representation, I show that minority representation at the local level alone does not increase the transfer of public goods to minority castes. Instead, I find more transfers when there is minority representation at both local and intermediate levels of government. Finally, I show policy-relevant heterogeneity effects coming from electoral motivations of intermediate level representatives and tastes for own caste under a decentralized government. The second chapter examines the horizontal aspect of local governance using India's vastly different rural and urban local government structures. There have been increasing voices that rural local governments lack capacity to govern areas with burgeoning population. I test if this is true and whether local governance affects access to public services, such as treated tap water and closed drainage, in general. To do this, I compare public goods provision between rural and urban local governments after controlling for observables, level of urbanization, and fixed effects. Importantly, I create an objective measure of the extent of urbanization with daylight satellite data and population data. I find that despite the inclusion of these controls and fixed effects, there are positive and statistically significant effects of having an urban local government. I also provide results for placebo tests that show government structure does not directly impact access to private services. Finally, I explore financial decentralization of local governments as a channel.

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1.1. Introduction

> Too often, services fail poor people in access, in quantity, in quality. But the fact that there are strong examples where services do work means governments and citizens can do better. How? By putting poor people at the center of service provision: by enabling them to monitor and discipline service providers, by amplifying their voice in policymaking, and by strengthening the incentives for providers to serve the poor. *World Bank Development Report* (Devarajan and Reinikka (2004))

Unequal access of resources for underprivileged minorities has been an ever-important political issue. A common solution used by policymakers is political representation, and this tool is thought to be more feasible with political decentralization. According to the International Institute for Democracy and Electoral Assistance (IDEA), there are 130 countries with constitutional, electoral or political party quotas as of 2020. For example, in Peru, 15 percent of candidates in 11 out of 25 regions are required to be members of native communities (Htun (2004)). However, whether more representation of the underprivileged can help level the playing field remains a debated question both theoretically and empirically, especially when cooperation across multiple levels of government is required.

In this paper, I investigate the effects of political representation at multiple levels of government on distribution of public services to the underprivileged. This is a departure from existing literature and policy discussions, which primarily focus on a single level of representation. Decentralization is considered to be suitable for ethnically or socially diverse developing countries where preferences are heterogeneous and information is more easily shared at the local level (Gadenne and Singhal (2014)). Moreover, governmental programs seldom get executed directly from a single level of government.[1] Yet little is known about the effects of representation across *multiple* levels of government on distributive politics. Some key roadblocks are the lack of random variation in group representation at multiple levels of government and lack of group-level data that can explicitly show distribution to poor minorities. I overcome these challenges in the context of India's federal system.

First, I leverage India's political reservation system that mandates representation of lower castes as a source of exogenous variation in group representation. The caste system is a hierarchical social structure that perpetuates deprivation of those in lower castes. Moreover, as an ethnically and socially diverse country, India promotes decentralization as a way to improve public services delivery (Bardhan and Mookherjee (2006)), leading to multiple levels of government. While the castes of representatives are not random, the reservation system that operates *separately* at each level of the government creates variation in caste alignment. At times, the castes of representatives are "aligned" (e.g. when multiple levels of representatives are lower caste) or "misaligned" (e.g. when local representative is lower caste and intermediate is upper caste).

Secondly, I use detailed data from India's National Rural Employment Generation Scheme (NREGS), which produces detailed data of the subsidized jobs allocated with caste information. NREGS is one of the largest welfare schemes in the world and, like many other schemes in India, it is administered at the local level to better target socioeconomically vulnerable households. The total number of jobs or local capacity is determined by the intermediate government and the allocation to households by the local government. Hence, the final allocation of NREGS jobs depends on the interaction of these two levels of government.

[1] For example, in the United States, public schools are funded through states and school districts, where considerable discretion from states and school districts determine the final allocation of funding to each school.

With local level panel data by caste, I measure the difference in changes in NREGS jobs allocated over time between constituencies that become reserved for lower caste and those that do not. I then compare these difference-in-differences for local constituencies that have a lower caste reserved intermediate representative to local constituencies without intermediate lower caste reservation, thereby measuring triple-differences. In other words, I compare the effects of lower caste representation when there is misalignment across levels to the effects when there is lower caste alignment. I define lower caste as Scheduled Caste (SC) in this paper due to their history of discrimination and minority status.

Using monthly sum of days generated within a local constituency, I find that SC representation at the local level with caste misalignment does not affect transfer of subsidized jobs to SC households. On the other hand, with both SC local and intermediate representation, SC households experience an increase of NREGS work in a given month compared to when only the local level is SC. This increase accounts for approximately 17 percent of the monthly SC work-days. Results show that with a non-SC intermediate representative, the overall capacity of NREGS distribution decreases for areas with SC local representatives, suggesting the importance of political hierarchy.

To understand these results, I explore three sources of heterogeneity: electoral motivation, taste for own caste, and better information within caste. Electoral motivation can affect distribution if politicians use public programs to increase their chances for re-election. Following literature that finds heightened effects of electoral motivation with more political competition, I use difference in vote share between the winner and runner-up from previous election to measure political competition. Evidence suggests that intermediate representatives distribute more jobs to caste-aligned local areas when there is greater competition, consistent with Dixit and Londregan (1998) and Arulampalam et al. (2009). Becker (1971) suggests that taste for own-group can affect allocation patterns. With greater weight put on utility of own-group members, a utility maximizing representative may allocate more to own-group members. I find that an event that increases the salience of castes can increase distribution to own-caste, suggesting that taste may be another channel as in Hjort (2014) and Shayo and Zussman (2011). Finally, I explore the channel of better information within own-group. If the channel is less information friction in own-group, we can expect better targeting for own-group households. I use jobs going to poorer households as a measure of better targeting and do not find evidence of better targeting despite better information being one of the arguments for decentralization.

This paper extends the literature on the effects of representation and diversity on transfers to the poor in a few ways. First, I shed light on conflicting results surrounding the effects of representation on policy. Theoretically, Hotelling (1929) and Downs (1957) suggest that the identity or preferences of a representative should not affect policy. Following the spatial competition and median voter theorems, a score of empirical papers have found that representation does not necessarily lead to promotion in an elected official's status (Ferreira and Gyourko (2014); Jensenius (2015)). On the other hand, "citizen-candidate" models developed by Osborne and Slivinski (1996) and Besley and Coate (1997) predict that politicians will implement their preferred policies. Hence, minority representation should lead to policies preferred by the minorities. Accordingly, Chattopadhyay and Duflo (2004) and Beach et al. (2019) find empirical results supporting this view.

Even within papers studying India's political quota, results are inconsistent across settings, levels of government studied, and goods or services provided. For instance, Pande (2003) shows that state-level political representation of minority castes improves transfers of benefits to them. Also, Saad et al. (2020) find that areas with high minority caste population that are politically protected give greater access to NREGS jobs to the minority caste. In contrast, Dunning and Nilekani (2013) and Jensenius (2015) find no evidence of improvement in access to transfers for targeted minority castes from reservation. These conflicting results demonstrate the need to find sources of heterogeneity, and this paper speaks to that issue. [2]

My work also relates to the literature on how political misalignment across tiers of government affects transfers. Typically, these studies show that the upper-level government provides more transfers to lower-level governments for re-election purposes (Dixit and Londregan (1998); Arulampalam et al. (2009); Gupta and Mukhopadhyay (2016); Bracco et al. (2012); Asher and Novosad (2017); Solé-Ollé and Sorribas-Navarro (2008)). I am not aware, however, of studies that can trace the final allocation to households by group as in this paper.

Finally, this paper speaks to a body of work examining how diversity affects public goods and services allocation. While these papers show a negative relationship between diversity and public goods provision, (Easterly and Levine (1997); Alesina and Spolaore (1997); La Ferrara (2003); Miguel (2004)), to my knowledge, they do not consider heterogeneity coming from multiple tiers of government. I find that diversity does affect public goods distribution negatively, but that with intergovernmental alignment, favorable allocation to underprivileged minorities is possible.

I also make a contribution to NREGS data by collecting one of the largest and detailed monthly panel datasets. There have been many studies looking using NREGS data (Aiyar and Samji (2009); Corbridge and Srivastava (2013); Niehaus et al. (2018)). However, most micro datasets are cross sectional and datasets spanning multiple years are at a coarser geographical level. By scraping data directly from the NREGS website, I am able to construct

[2] Sharan and Kumar (2019) does directly discuss the effects of "mismatch" in intergovernmental representation. However, the lower level representatives discussed in the study have negligible roles in actual allocation of public services. In fact, lower level representatives here are closer to proxies for the area's group (in this case, caste) composition. Hence, the results are more akin to presence of in-group bias.

a balanced panel dataset spanning eight years for 7,584 unique local constituencies.

Although the setting of this paper is India, decentralization with socioeconomic diversity is not isolated to this setting. Instead decentralization has been a global trend for lower-income countries in the past three to four decades (Bardhan and Mookherjee (2006)) and many high income countries like the United States are heavily decentralized. Decentralization allows minority representation to be more feasible, but the question is if creating a seat for minorities is enough. I find that rather, political hierarchy and representation at more than one level of government determine the extent to which minority representatives can assist the underprivileged. Hence, if policy makers in decentralized countries want to enhance the status of poor minority groups, it is crucial to consider representation at more than one level of government.

The remainder of this paper is organized as follows. In section 1.2, I provide institutional background on the caste system, India's governmental organization, and specific roles relevant representatives play in NREGS job allocation. In addition, I will give a more detailed account of the history and characteristics of NREGS. In section 1.3, I introduce a conceptual framework that can help us understand why political hierarchy and group can affect redistribution. Section 1.4 discusses the data used. I lay out my empirical strategy of triple-difference in section 1.5. Section 2.4.1 shows results and section 1.7 discusses heterogeneity analyses with policy implications. Finally, in 1.8 I conclude.

1.2. Background

1.2.1. Caste System

The caste system is a form of social stratification that has endured for more than 3,000 years[3] It categorizes Hindus into four groups – Brahmins, Kshatriyas, Vaishyas, and the Shudras, listed in order of hierarchy. The minority group I focus on in this paper, Scheduled Castes (SC), was below and outside of the caste system entirely; members of this caste were historically called "untouchables." The caste system was closely tied to occupation, and SC mainly worked as sewer and toilet cleaners. There was also residential segregation where lower and upper castes did not even share a well. According to the 2001 Indian census the SC population accounts for 16.2 percent of the total population with about 166 million identifying is SC.

Years of historical discrimination has left lower castes behind socioeconomically. In order to give lower castes opportunities, India instituted mandatory quota or reservation systems for lower castes across schools, jobs, and politics. Importantly, for this paper, political seats across multiple tiers of India's decentralized government are reserved for the lower castes. While caste-based discrimination is no longer legal, the remnants of its effect remain as people continue to identify themselves with their castes. Voting along caste-lines is common and there were 48,935 cases of hate crimes targeting scheduled castes in year 2018 and only about five percent of all marriages were inter-caste. [4] Economically, about 84 percent of highest earners in SC rural households makes less than 5,000 rupees a month (about 60 USD) while approximately 70 percent of non-lower caste households belong to this category according to the Caste Census in 2011. Moreover, as of 2011, 66 percent of SC were literate compared to the population average, 73 percent.

[3] There, however, has been scholarship showing that the caste system was institutionalized in the mid to late 19th century with British colonization of India.

[4] National Crime Records Bureau in India

1.2.2. NREGS

The Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) is an Indian labor law and social security measure passed in 2005 and aims to improve livelihood security in rural areas. The Act created Mahatma Gandhi National Rural Employment Guarantee Scheme (NREGS), the scheme under which rural jobs are distributed. NREGSs "guarantees" at most 100 days of rural work in a financial year to every rural household. It is the largest public works program in the world, providing employment to some 50 million rural households and affecting the lives of up to 250 million individuals. [5] Moreover, the Indian government is planning to spend Rs 660 billion or US$8.9 billion on NREGS for the 2020-2021 financial year.[6]

NREGS expanded to all of India starting in 2008. The jobs provided are unskilled in nature and try to aim for creation of public goods or assets. Some examples can be removal of weed and construction of government assisted housing. On average, households that work NREGS jobs can earn around 40 percent of their monthly income through the program. The administration of the scheme occurs at the gram panchayat level, the smallest rural political unit in India. The costs of the scheme is shared between the Center and the state and the budget is decided at the state level at the beginning of each financial year. Yet, to reach state approval the budget has to go through the approval of each tier of the rural government first (there are three tiers). For a household to get a job through the scheme, they must obtain a job card at the local gram panchayat's office. Workers then can apply for work and local officials allocate the jobs. If jobs are not available, unemployment benefits are to be given, but this rarely happens. While NREGS is meant to "guarantee" every rural household employment, in reality, the program is supply driven. As a result, allocation heavily depends on program officers that are responsible for overall monitoring

[5] 250 million is about 67 percent of the population of the United States and double the population of Mexico. `https://www.theigc.org/blog/misleading-attack-on-mnrega/`

[6] `https://www.indiabudget.gov.in/doc/Budget_at_Glance/bag1.pdf`

and implementation of the scheme and the sarpanches, who are responsible of the job allocation at the gram panchayat level.

1.2.3. Local government structure

With the passage of the seventy-third and seventy-fourth constitutional amendments in 1994, India granted local governments with constitutional status and required regular local elections. The goal was to devolve enough power and resources to local governments so they can function as self-governments. Importantly, much weight has been put on the local governments' responsibility to provide public services, implement poverty alleviation programs, and promote distributive equity (Bardhan and Mookherjee (2006)). I consider two key political positions that have heavy influence over allocation of NREGS jobs: members of legislative assembly (MLA) and sarpanches. The MLAs are part of the state legislative assembly (Vidhan Sabha) and sarpanches are head of gram panchayats, where gram panchayats are India's smallest self-governing unit. The hierarchy of the government structure is represented in Figure 1.1. The two levels in focus are denoted with red boxes around them. Key here is that the MLAs are hierarchically above sarpanches. Figure A.1.1 shows assembly and gram panchayat boundaries in the state of Rajasthan in India. Rajasthan is one of the larger states in India with strong emphasis on agriculture. The figure shows the relative geographic size of assemblies compared to gram panchayats.

MLAs are directly elected to the state parliament every five years. There may be concerns about partisan bias in MLA reservation boundaries and status, but they are decided by India's Delimitation Commission in accordance to the census. The current borders are based off of the 2001 Indian census. There are overall 4,121 legislative assembly seats in India and each state must have at least 60 and no more than 500 members in each state with some exceptions. The number of assembly seats each state are designated depends on the state's population. As a legislator, the MLA plays an important role in enacting or opposing new laws for the state. MLAs also have financial power in the state assembly and provide consent to the budget and expenses made from the state treasury. [7] For MLAs, NREGS is an important political tool that is used as "election winning devices" according to Maiorano (2014). Furthermore, MLA elections are usually competitive, encouraging MLAs to work for votes. MLAs affect NREGS jobs distributions in two main ways. First, MLAs influence the appointment of field/block officers (hired on a contract basis), who implement NREGS alongside with the sarpanch. Studies also find that MLAs may manipulate the selection of works (Aiyar and Samji (2009)), lobby for certain projects that are more visible, or target politically valuable communities Maiorano (2014). Beyond the influence through block officers, MLAs also affect the NREGS budget. The shelf of works for NREGS jobs and labor budget have to be approved by the block panchayat and the state government before every financial year, and MLAs have power in both levels.

The sarpanch represents her gram panchayat and is the point of contact between intermediate level government officers and the village community. A gram panchayat consists of a group of villages, and each gram panchayat consists of on average about 420 households. The sarpanch is typically elected every five years either by the village council (Gram Sabha) or directly by the villagers. The sarpanches also depend on partisan politicians, such as MLAs for funds for pork projects (Schneider (2014)). There, however, are large differences in how active a sarpanch is depending on the state. In terms of NREGS implementation, the sarpanch is theoretically the final allocator of NREGS jobs. A worker who wants NREGS jobs must physically apply at the council office. Plans and decisions regarding the nature and choice of works are made in open assemblies of the Gram Sabha and ratified by the sarpanch with the oversight of the block officer, a local bureaucrat. Even though allocation decisions are supposed to be joint decisions of the council, in practice sarpanches make the decisions either themselves or jointly with their spouse (Jeong et al. (2019)). Figure 1.2 shows the relationship between MLAs and sarpanch in relation to NREGS job allocation

[7] http://timesofindia.indiatimes.com/articleshow/71241197.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst

decisions schematically.

1.2.4. Gram Panchayat Reservation

Across most gram panchayats in India, sarpanch is subject to caste reservation. When a seat is reserved for a particular caste, only candidates in that particular caste are eligible to run for election [8]. By reserving positions of power for underrepresented castes, this system aims to give more voice and power to the minority castes as it is rare for a minority caste to win seats in absence of reservation due to the voting pattern following caste lines.

While the exact reservation rules differ by state, states commonly rotate gram panchayats to be reserved, meaning not all gram panchayats are reserved and the selection of gram panchayats that are reserved change each local election. Gram panchayat reservation decisions are made at the the block level, which are composed of several gram panchayats[9]. The number of gram panchyats to be reserved per block is proportional to the *block-level* fraction of the caste to be reserved. For example, when determining the number of gram panchayats to reserve for schedule castes, if 40% of the block population is scheduled caste, 40% of the gram panchayats should be reserved. The population is to be taken from the most recent existing round of census data. Gram panchayats are listed in descending order of their fraction or population of scheduled caste and from this ordered list, gram panchyats are reserved in order from the top each election. Each local election prompts rotation of reservation. For instance, if the first five gram panchayats from the list were reserved this term, in the next local election, the next five gram panchayats are reserved. While these are the official rules, implementation itself can vary across districts. Moreover, the lack of publicly available official gram panchayat-level population data makes it difficult to assess the exact compliance.

[8] There are exceptions like gram panchayats in scheduled areas.

[9] In my sample of 10 districts in Uttar Pradesh and 5 districts in Rajasthans there are on average around 44 gram panchayats within a block

I illustrate this process through a mock example of scheduled caste reservation rotation in Table 1.1. Here, we will assume that this block consists of 40% scheduled caste – this means that 40% of the gram panchayats should be reserved. In this example, there are ten gram panchayats, so four gram panchayats should be reserved. Column "pop SC" has scheduled caste population and the "theory reserved 2010", "2015" show whether a gram panchayat should be theoretically reserved ("Y") or not ("N") in election years 2010 and 2015 respectively. Note that the gram panchayats have been listed in descending order of SC population. In 2010, we see that the first four are theoretically reserved. In 2015, the next four gram panchayats are reserved, and this pattern continues on, with 2020 having the last two (I, J) and first two gram panchayats (A, B) reserved. This rotation rule naturally ensures that a gram panchayat does not get reserved for consecutive terms[10].

1.2.5. Assembly Reservation

Since 1950, seats in the Indian Parliament and state assemblies were reserved proportional to their share of the minority caste population. In each Indian state and about 20 percent of assemblies are reserved. Unlike gram panchayat reservations that rotate, the reserved assembly constituencies remain stable over year other than infrequent changes in boundaries by the delimitation commission according to population changes. The last update occurred in 2008.

Crucially for my paper, caste reservations for the sarpanch and MLA occur independently. Consequently, there are times that reservation of the gram panchayat and asembly are "in sync" where both positions are reserved for SC and other times where SC reservation is only at one or none of the levels. Changes of alignment in castes of sarpanch and MLA vary over time and geography will be used for my empirical strategy of triple-difference and will be discussed further in section 1.5.

[10] India's Supreme Court capped reservations at 50 percent.

1.3. Conceptual Framework

In this section, I explain the intuition behind why caste misalignment can matter for redistribution, in particular of NREGS jobs, to minority castes. Figure 1.3 schematically shows how NREGS jobs can be allocated in a decentralized government like India's. (S) refers to SC and (N) non-SC. The numbers represent jobs to be distributed. "Intermediate" refers to MLAs in this case, and "Local" refers to sarpanches. The last row demonstrates final allocation to households by caste. For purposes of this example, we will assume that representatives at both levels distribute more jobs to own-caste at a 4-to-1 ratio. While this paper does not directly uncover the *cause* for this pattern. I will discuss sources heterogeneity that suggests possible factors that affect the distribution. The left hand side of the tree represents allocation process for an SC MLA, who has 100 jobs to allocate. Within the constituency of this SC MLA, there are gram panchayats with SC sarpanch and non-SC sarpanch. MLAs cannot directly target households but can target gram panchayats using sarpanch's caste. Since we assumed that more jobs go to own-caste, 80 jobs go to gram panchayats with SC sarpanch and 20 to the rest. Now, within a gram panchayat, there are SC households and non-SC households. Focusing on the SC sarpanch, 64 out of 80 jobs go to SC households following the previous assumption. On the right hand side of the tree MLA is non-SC as illustrated. This time, out of 100 jobs, 80 jobs go to non-SC sarpanch while 20 go to the SC sarpanch. Again, looking at the gram panchayat with SC sarpanch, 16 out of 20 households go to SC households and 4 to non-SC. Although in both cases there is local minority (SC) representation, depending on the caste of the intermediate representative, or the MLA, final allocations to SC households can be very different. With SC representation at both levels (on the left hand side), SC households receive 64 jobs whereas with SC representation at only the gram panchayat level, SC households receives 16 jobs. This simple example shows that minority representation at one tier of government alone does not necessarily lead to greater public service access to minority households. Rather, with the combination of decentralization and greater distribution to own-group, minority representation at one level without group alignment with other tiers can *negate* efforts to redistribute to minorities. While not the focus of this paper, we also see that for the non-SC households the same story applies. That is, with non-SC alignment comes greater allotment to non-SC households.

Why might we expect more distribution to own-group? I discuss channels of taste, electoral motivation, and information. These channels, in the context of a multi-level administration system can give insight into why group misalignment can affect redistribution. It is important to understand why distribution can be affected by each of these factors as governments can evaluate appropriate policy changes to increase transfers to minorities if that is their goal.

First I will examine the channel of taste. Following Becker (1971) more transfers to own-group can occur due to taste for own-group members. Politicians can put higher weights on utilities of own-group members relative to others who are not. Assuming utility is increasing in transfers, a utility maximizing politician then would direct more transfers to own-group. Empirical papers applying this theory have found results consistent with the theory in lab experiments (Charness and Rabin (2002); Chen and Li (2009)) and team production in private sector (Hjort (2014)). In this paper's setting, if representatives prefer own-caste, there would be larger transfers from MLAs to own-caste sarpanches and larger transfers from sarpanches to own-caste households as predicted by the example in figure 1.3.

Electoral motivation can be another factor affecting allocation, meaning politicians may use NREGS as a political tool. According to Dixit and Londregan (1998) and Arulampalam et al. (2009), incumbent politicians may be interested in their own re-election. Also, they may be interested in promoting own-group politicians as their stronger presence can lead to better performance for incumbents as well. Politicians would prefer to direct resources to clearly identifiable groups to maximize chances of election. Exerting the same effort, politicians can more effectively "swing" voters by targeting groups with larger marginal utility from redistribution. In this case, the marginal group is the SC households. Moreover, MLAs understand that misaligned sarpanches will allocate jobs in a way that is more beneficial to the sarpanches' own group. Following this mechanism, with higher electoral competition we can expect stronger effects of targeting (Arulampalam et al. (2009); Cascio and Washington (2014); Gupta and Mukhopadhyay (2016)). This follows figure 1.3's pattern of larger transfers from intermediate representative to SC local representatives with alignment. In this paper's setting, the minority caste local representatives, or sarpanches, have little electoral motivation as (1) it is difficult to be elected without caste reservation and (2) the same gram panchayat is unlikely to be reserved for the very next term. Hence, I will abstract away from electoral motivation coming from sarpanches and focus primarily on the electoral motivation of the MLAs.

Better information flow within own-group can also explain more transfers to own-group. If local representatives are more aware of the needs of own-group households and the intermediate representatives more aware of their own-group local representatives, there can be relatively more accurate beliefs regarding the transfer needs of own group (Bohren et al. (2019)).With the channel of better information, or less information friction, we can then expect better targeting within own-group. I will empirically go over these three channels in section 1.7.

1.4. Data

This paper merges key three datasets: (1) NREGS panel data at the month, gram panchayat, and caste level (2) gram panchayat reservation panel data at the gram panchayat and election year level, and (3) assembly level cross sectional reservation data at the assembly level. I will explain these three datasets first, then describe the population census, caste census, and geographic boundaries data. The final sample is a balanced panel dataset that includes 11 districts from Uttar Pradesh and 5 districts from Rajasthan for years 2012 to 2019. The sample includes 103 unique assemblies and 6126 unique gram panchayats. My sample is limited to these districts and years due to data availability and the districts were selected at random[11]. Both are large northern states in India with heavy reliance on agriculture and active political decentralization. Uttar Pradesh is the largest state in India by population with the largest number of poor in India. Rajasthan is the seventh most populous state and while it made great strides in reducing poverty, around 15 percent of its population is still below poverty line. With large demand for NREGS jobs, both states also actively implement NREGS, making it ideal places to study.

1.4.1. NREGS

The NREGS dataset I have compiled contains total days of work generated through NREGS and the monthly number of households that worked at the gram panchayat level. The variables come from the NREGS official website where each individual's job card is uploaded.[12] The job card is at the household level and lists the household members that are registered to work, work applications, offered works, and actual work completed alongside with the number of days applied and worked, and amount of money the household is owed and paid. In addition to work information, the job card includes information on household's caste and whether the household is below the poverty line. Below poverty line (BPL) households are government designated and apply to households that earn less than a set level of income. The BPL level is set nationally for rural and urban areas separately. Job cards also denote state, district, block, and gram panchayat information, which have to be matched by name with other datasets. By collecting data directly from individual job cards, I am able to have detailed data spanning multiple years. While many scholars have collected NREGS data over years, my data's level of detail, frequency, and panel nature make it unique. Specifically, high frequency panel data with caste information are rare in India.

[11]The sample districts are districts that I have finished scraping and cleaning the data first. The order of which district I started was selected at random.
[12]`https://nrega.nic.in/Netnrega/stHome.aspx`

There is controversy over how accurate NREGS data are as people fear "ghost workers," where false jobs and workers are recorded, or incomplete data entry. If there is more collusion when there is intergovernmental alignment and thus, more ghost workers, there can be an upward bias in the effect of group alignment estimation. Through heterogeneity analyses, I show that my results are not driven by this channel.

In fact, the most glaring issue with the data is that it does not measure demand accurately. Officials generally only record instances where work was actually given. Hence, while it looks like most applicants are granted work, we in fact do not know how many actually applied. Furthermore, anecdotally, households don't "apply" for jobs as they do not know when jobs will be available. Instead they are often offered jobs by the sarpanch when there is availability. Hence, I do not attempt to measure demand directly from the NREGS data.

1.4.2. Reservation

The gram panchayat reservation data contains reservation status at the gram panchayat level for each local election cycle. While there are differences across states, the data typically includes name of sarpanches, their caste, and reservation status. In my sample, there was a local election in 2010 and 2015 for Uttar Pradesh and 2011 and 2016 for Rajasthan. There is no centralized source of local elections information. Rather some states publish their election data on the state election commission website. MLA election data on the other hand is publicly accessible from India's election commission and includes information on candidates running, their castes, party, votes they received, and reservation status.

I intersect assembly geographic boundaries data with 2001 village-level boundaries data that I aggregate up to the gram panchayat level. The assembly boundaries come from Creative Commons Attribution-ShareAlike 2.5 India and the 2001 village boundaries come from New York University Spatial Data Repository.

1.4.3. Census Data

Demographic data is sourced from India's census conducted in 2001. Census variables include population by caste, size (area), literate population, number of primary schools, and so on. The census is conducted every ten years. India's census data is provided at the village level, which is a building block of gram panchayats. As the unit of analyses is at the gram panchayat level, I aggregate the data to gram panchayat level, which is a nontrivial process as much of it relies on matching by name.

1.4.4. Caste Census

Finally, I collected income data by caste from the Socio Economic and Caste Census 2011. While this data does not provide exact income, it breaks down the income of households' highest earner to one of three income brackets by caste. The three categories are below 5k rupees, 5k-10k rupees, and above 10k rupees average monthly income. 5k rupees correspond to about $60 US. The middle category of 5k-10k rupees can be roughly thought of as the lower end of middle income in India.

1.4.5. Merging Datasets

Generally, gram panchayat level data in India do not have numeric identification codes, which means that datasets must be merged using gram panchayat *names*. However, gram panchayat names are often spelled and denoted differently across years and datasets, making it difficult to achieve perfect matches. In order to merge the datasets that are given in different geographic units, I create concordance between village and gram panchayats using the high-resolution Rural-Urban Geographic Platform for India (SHRUG) dataset (Asher et al. (2019)) and the Local Government Directory (LGD) [13]. The SHRUG data organizes census data with unique identifiers called *shrid*, which describe stable units of area overtime and can be merged into India villages easily. The LGD data includes a crosswalk between villages and gram panchayats names. The two datasets combined act as my concordance

[13] `https://lgdirectory.gov.in/`

key where I use fuzzy matching to connect gram panchayat level data with my concordance data.

1.4.6. Sample

For my analysis I use gram panchayats for which I have information throughout both rounds of panchayat election. This leaves me with a balanced panel for Uttar Pradesh and Rajasthan. I exclude scheduled areas, as political posts are *always* reserved for scheduled tribes, which is not discussed in this paper.[14] Statistics for the sample at the gram panchayat level are in Table 1.2. Table 1.2 panel A contains baseline demographic data on gram panchayats and panel B, NREGS outcome variables. The baseline data come from SHRUGS, 2001 census data, and 2011 caste census (for the number of households by caste). The first two columns of the these two tables show the average and standard deviation for the overall sample, the next two are by MLA reservation status, and the last two by sarpanch reservation status. Standard deviations are in parentheses.

There are around 5-10 villages per gram panchayat and around 40-130 gram panchayats within an assembly. Table A.1.1 shows detailed statistics about the number of households and population for the sample. The households data comes from the 2011 caste census and the population based on the 2001 census. On average about 24 percent of the gram panchayats are reserved for SC in my sample and 22 percent are included in assemblies reserved for SC. At the mean, we see that gram panchayats that are in SC reserved MLAs are smaller and have a higher fraction of SC population compared to those in MLAs not reserved for SC. Similar goes for gram panchayats reserved for SC compared to those not reserved for SC.

In Table 1.2 panel B, I examine total number of households that work in a given month and gram panchayat. I further break this down by the SC households and non-SC households.

[14] Scheduled tribes are not discussed for two main reasons. First, many gram panchayats simply do not have any scheduled tribe households. Secondly, some states do not have caste reservation for scheduled tribes. For example, in Uttar Pradesh, no assembly is reserved for scheduled tribes.

On average around 25 households work monthly, which is about 6% of all households. We also see that SC households, on average, are more reliant on NREGS jobs. Although SC households are about a quarter of the total households, about a third of all NREGS work is done by SC households. Total worked days is a sum of all the days of work generated within a month and gram panchayat. It reflects the total amount of work generated monthly at the gram panchayat. This variable is also divided into whether these days were worked by SC households or not. Approximately 367 total work-days are generated, of which about 99 days are worked by SC households.

1.5. Empirical Strategy

With randomization of castes at both levels, we can simply look at the interaction effects of the sarpanch and MLA's castes. Given that this is not the case, a naive regression could be subject to omitted variables bias. For example, gram panchayats with both SC sarpanch and SC MLA might be places where SC have more political power. In this case, the representatives' caste can be measuring the political power of SC rather than the effects of alignment in representation. Also, we can imagine that SC representation at both levels can signify higher levels of poverty, which means that we may be measuring the effects of greater demand. In both cases, the effects of SC alignment in representation will be biased upwards.

To get around this problem, I employ a triple-difference strategy using caste changes driven by political reservation. In my sample period, there were local elections for both Uttar Pradesh and Rajasthan. Moreover, only some gram panchayats have assemblies reserved for SC. This setting creates three components that enable a triple-difference strategy: (1) gram panchayat reservation changes across geography for each term *independent* of assembly caste reservation; (2) gram panchayat reservation changes *over time* as the rules do not permit consecutive reservation for any gram panchayat; and (3) assembly reservations status vary across location. I will show that my setting satisfies parallel trends assumption through graphical analyses in section 2.4.1.

Figure 1.4(a) illustrates an example of how local reservation can rotate over time. Each rectangle represents a gram panchayat and the borders signify boundaries of gram panchayats. SC and NSC each denote gram panchayats reserved for SC and not reserved for SC, respectively, and the SC reserved areas are colored in blue. The numbers in parentheses show the SC population for the gram panchayats. The left side of the figure is at $t = 0$ and the right half is at $t = 1$, which is after a local election. In the left side of the figure, we see that the gram panchayats with the three largest SC population are reserved for SC. Post election, at $t = 1$ we see that three gram panchayats with the next largest SC populations are reserved. In sum, we see there is variation in both time an geography in gram panchayat reservation. Next, panel (b) of figure 1.4 shows the same figure as (a) but with a focus on assembly borders shown in thicker lines. The thick red solid borders highlighting the first two columns of gram panchayats show the SC reserved assembly. The last column with thick black borders is a non-SC reserved assembly. There are few noteworthy points. One is that unlike sarpanch reservation, MLA reservation remains stable over time. Next, I shaded gram panchayats that have both SC sarpanch and MLA. We see that while the first two gram panchayats in the first row are shaded in $t = 0$, in $t = 1$, two different gram panchayats are shaded. In other words, due to the rotating nature of gram panchayat reservations, caste alignment of representatives vary over areas and time.

With these variations in hand, I can estimate the following:

$$\begin{aligned} Y_{ijst} = \beta_0 &+ \beta_1 post_{st} \times localSC_{ijst} \times InterSC_{ijs} \\ &+ \beta_2 post_{st} \times localSC_{ijst} + \beta_3 post_{st} \times InterSC_{ijs} + \eta_{ijs} + \delta_{st} + \epsilon_{ijst} \end{aligned} \tag{1.1}$$

Data is at the gram-panchayat, assembly, state, and month-year level, where Y_{ijst} is the outcome variable of interest measuring NREGS job distribution in gram panchayat i, assembly j, state s, and month-year t. The main outcome variable I analyze is the total number of work-days generated in a given gram panchayat-month-year. I will further break down the total days into those worked by only SC households and those by non-SC households. $post_{st} = 1$ if the month-year is after the sarpanch election (i.e. after the 2015 Uttar Pradesh election and 2016 after the Rajasthan election). $localSC_{ijst} = 1$ if gram panchayat i is becomes reserved for SC. $InterSC_{ijs}$ is an indicator for gram panchayat i belonging to an SC reserved assembly j. Note that the MLA status does not vary by time. η_{ijs} are gram panchayat level fixed effects and δ_{st} state-date fixed effects. With gram panchayat fixed effects, I am able measure variation *within* gram panchayats.

β_1 is the coefficient of interest and shows triple-difference effects. It measures the *differential* effect of a gram panchayat becoming reserved SC in an SC reserved assembly compared to the effect in a non-SC reserved assembly. In other words, we can see if there is a statistically significant difference in effects of SC gram panchayat reservation if there is caste alignment across the two tiers of the government or not. β_2 measures the difference-in-differences effect of gram panchayat SC reservation when it belongs to a non-SC reserved assembly. $\beta_1 + \beta_2$ is the difference-in-differences estimate of being reserved for an SC sarpanch when MLA is also SC. Note that all estimations correspond to intent-to-treat effects as I am using reservation status rather than actual caste of the representatives. All standard errors are clustered at the assembly level as outcome residuals are likely to be correlated for gram panchayats within a same assembly.

1.6. Results

The triple-difference estimates based on equation 1.1 are in Table 1.3, where the first column shows results for all monthly NREGS work-days regardless of caste, and column (2) and (3) broken down into days worked by only SC households and non-SC households respectively.

The richness of the NREGS data allows me to explore exact benefits constituents receive depending on their caste. Note that the outcome is the sum of days generated within a gram panchayat monthly. It is different from the per-capita number of days of work. All estimates include state-time fixed effects for state-specific time trends and gram panchayat fixed effects for within gram panchayat comparisons. I report outcome variable means and number of unique gram panchayats as well.

The interpretation of column (1)'s coefficient on $localSC \times post$ is as follows: when a gram panchayat has a non-SC MLA, SC reservation of a gram panchayat leads to about 54 ($p<0.01$) fewer total days of work monthly compared to when there is non-SC reserved sarpanch and MLA. That is, overall, with intergovernmental misalignment fewer work-days are generated. The triple-difference coefficient explains if there is a differential effect within a given gram panchayat from SC reservation of gram panchayats when their assemblies are also reserved for SC. Column (1)'s triple-difference coefficient shows us that the effect of gram panchayat SC reservation is 37 work-days larger on average when there is caste alignment compared to when there is not. I've discussed how the *overall* supply of jobs changes with misalignment, but we are more interested in what happens to the minority caste, SC, households.

Column (2)'s second row demonstrates us that there are no statistically significant effects to SC households from having a SC reserved sarpanch when the MLA is non-SC. This result is important as it matches results from papers that do *not* find effects of sarpanch reservation[15]. It is possible that these findings come from heavy sampling from non-SC assembly areas. However, we see from the triple-difference coefficient that with SC alignment in both levels, there are 17 ($p<0.05$) more SC work-days generated. This is approximately 17 percent of the average SC work-days. This implies that local representation of minority

[15] E.g. Dunning and Nilekani (2013) and Jensenius (2015)

castes can increase transfers to minority castes conditional on there being caste alignment with the upper-level government, or the MLA. Finally, column (3) gives us an insight into how SC work-days are unaffected with caste misalignment when there is an overall decrease in total work-days. We see from the second row that non-SC households work about 58 ($p<0.01$) fewer work-days with SC sarpanch reservation and non-SC MLA. It appears SC sarpanches shift jobs from non-SC households to SC households under a non-SC MLA. Overall, the results suggest that intergovernmental misalignment is associated with fewer work-days. Moreover, while minority representation can benefit minorities, but not when upper-level representation is misaligned with the lower-level representation. In A.1.2, the outcome variables is monthly number of households that worked NREGS job within a gram panchayat. The results show positive and significant SC alignment effects on number of households that worked NREGS households. Moreover, overall, more households work with SC alignment.

Given that I am analyzing data at levels, there might be concerns that the results can be driven by outliers. To address this potential threat, I analyze my data with outcome variables winsorized at the 99 percent level. While the coefficient size decreases, results remain significant and qualitatively the same as it can be seen in appendix table A.1.3, suggesting that the results are not driven by few outliers. Although gram panchayat fixed effects are included, hence, I use changes within gram panchayat, there may be concerns that the findings are coming from differences in population sizes. In appendix table A.1.4 I include baseline controls including number of total households, number of SC households, and physical size of gram panchayats interacted with the "*post*" indicator variable to allow differences in trends. The inclusion of these controls do not affect the results qualitatively and the findings remain significant.

I show these results graphically in an event studies setting in figure 1.5. "0" is the year of gram panchayat elections, hence the year of "treatment" for gram panchayats that become reserved for SC. I show three years before and after the election, years for which I have the full 12 months of data. The base or reference year is the year before sarpanch elections. While the effect sizes make the changes in trend not very transparent, we can confirm parallel pre-trends of the triple-difference estimates. The black solid lines show effects of SC reservation of gram panchayats for those with SC MLAs. The black dashed lines show the 90% confidence intervals. The red lines show effects of SC gram panchayat reservation for areas with non-SC MLAs and the red dotted lines correspond to the coefficients' 90% confidence intervals. The triple-difference coefficients correspond to the difference of these two lines.

In panel (a), I show results for sum of work days created. We see that, before election, the differences between the two lines are negligible and not statistically significant. While the triple-difference estimations are noisy, we see that after sarpanch election, gram panchayats reserved for SC under non-MLAs experience a significant drop in overall work-days and this pattern continues, suggesting an overall shrinking of the pie. This visualizes to the difference-in-differences result for non-SC MLAs from column (1) in 1.3. We do not see significant changes for SC MLA gram panchayats. In 1.5(b), I show event study results for SC households work-days. We similarly see parallel pre-trends before election. Unlike in panel (a), we do not see a dramatic decrease in SC work-days in non-SC MLA areas. Instead, there is a increase in SC work-days after SC gram panchayat reservation in aligned areas. The difference between the two coefficients are statistically significant a year after election, but the gap decreases over time. The minimal changes in trends for non-SC MLA areas correspond to the difference-in-differences coefficient from column (2) in 1.3. Finally, panel (c) shows results for non-SC work-days. We see that regardless of alignment, SC sarpanches lead to lower work-days for non-SC households. Overall, the graphs confirm parallel pre-trends and display similar qualitative results as the regression results in table 1.3. That is, representation of minority castes is effective in increasing transfers to minorities when there is also alignment in caste with the upper-level government. With misalignment, the overall capacity of NREGS distribution decreases, resulting in SC sarpanches not being able to allocate more jobs to SC households.

1.7. Heterogeneity Analyses

In this section, I describe possible sources of heterogeneity. I will discuss heterogeneity coming from electoral motivation, taste, and information.

First, electoral motivation can be affect jobs distribution since NREGS may be used as a re-election tool for politicians. An important point, however, is that gram panchayats reserved for SC are extremely unlikely to be reserved again in the election cycle directly after. Given voting patterns that usually follow caste lines and the fact that SCs are usually minorities, even at the gram panchayat level, there is a low chance for SC sarpanches to be re-elected. Consequently, it is difficult to claim that SC sarpanches have re-election motivations.

On the other hand, the incentives for SC MLAs are clearer as their reservation status stays stable over time. With MLAs being aware of the allocation patterns of the sarpanch depending on caste, it is more beneficial for MLAs to focus on gram panchayats with same-caste sarpanches as their efforts will have less "leakage." Additionally, given the lower economics status of SC, SC households are more "swingable" through NREGS jobs for their marginal utility of an additional job is likely to be larger than that of non-SC households. Under these assumptions an SC MLA can allocate more jobs that can translate to votes with an SC alignment. Thus, we would expect greater effects of SC alignment for SC households in areas with higher election competition. I measure political competition by the difference in share of votes between the winner and runner-up in the last MLA election. We would expect greater political competition with smaller vote-share difference. I use this measure of political competition for quadruple-differences:

$$
\begin{aligned}
Y_{ijst} =& \beta_0 + \beta_1 post_{st} \times localSC_{ijst} \times InterSC_{ijs} \\
& + \beta_2 post_{st} \times localSC_{ijst} + \beta_3 post_{st} \times InterSC_{ijs} \\
& + \beta_4 localSC_{ijst} \times d_{ijst} + \beta_5 InterSC_{ijs} \times d_{ijst} \\
& + \beta_6 localSC_{ijst} \times post_{st} \times d_{ijst} \\
& + \beta_7 InterSCijs \times post_{st} \times d_{ijst} \\
& + \beta_8 localSC_{ijst} \times InterSCijs \times post_{st} \times d_{ijst} + \delta_{st} + \epsilon_{ijst} \qquad (1.2)
\end{aligned}
$$

d_{ijst} is the vote difference and here the quadruple-difference coefficient is β_8. It captures heterogeneity of SC alignment effects coming from political competition. The results are in table 1.4. Again, the outcome variables are sum of work days created in a gram panchayat each month where column (1) shows the overall total, and columns (2) and (3) show work days for SC and non-SC households respectively. I report only the quadruple-difference coefficients for brevity. The number of observations and unique gram panchayats are smaller than that of table 1.3 as not all gram panchayats have election results. Column (2) shows that there is a statistically significant ($p<0.05$) and positive effect of political competition on SC work days for SC aligned gram panchayats. Specifically, a one standard deviation decrease in previous election's vote difference between winner and runner-up leads to 11 more SC work days with SC alignment. That is, more electoral competition and thus, more accountability, is correlated with more transfers to SC households in SC-aligned gram panchyats. We do not see meaningful changes in NREGS work allocation to non-SC households. Although quadruple-difference estimates are likely noisy, results for non-SC households show that effect sizes are rather small as well.

For the channel of taste, I test whether taste for own group affects job allocation. To test this hypothesis, I use caste protests that happened in April, 2018 and affected my sample states particularly [16]. The protests occurred against the supreme court's ruling that have said to weaken the protection of lower-castes. Importantly, protests, which lasted not more than a week should not have changed the need for jobs abruptly and differentially depending on caste alignment. On the other hand, it is possible that the animosity of SC against non-SC increased the salience of castes, amplifying effects of misalignment. Using an event that can increase group salience is a method Fisman et al. (2019), Hjort (2014), Shayo and Zussman (2011) also use to show the channel of taste. To observe responses right around the protest, I estimate effects of caste alignment right before and after protests in 2018, and compare these coefficients with that of other non-protest years, hence, estimating quadruple-differences.

The graphical results are in figure 1.6. Panel (a) shows event study results for total work-days generated, (b) SC work-days, and (c) non-SC work-days. The black lines correspond to coefficients for protest year (2018) and the red lines are for non-protest years post local elections. All coefficients are in relation to March as the protests happened in April. We are interested in the *differences* between the two lines. The only outcome that shows a clear differential pattern is work-days allocated to SC households. We see that a month after protest there is a large jump in SC work-days in SC aligned gram panchayats compared to misaligned areas during protest year compared to non-protest years. The changes are marginally statistically significant for May and months September through November despite the coefficients being quadruple-differences. We do not see significant differences between protest year and non-protest years for non-SC work-days. This is consistent with the channel of taste as an increase in caste salience can lead to more own-caste favoritism. It is possible that the animosity in caste relations affected employment of SC households, but it cannot explain why there would be differential effects depending on intergovernmental caste alignment.

[16] `https://www.bbc.com/news/world-asia-india-43616242`

Better information exchange between own-caste can also be a channel. That is, perhaps, there is better information share between sarpanches and households or sarpanches and MLAs in the same caste. Given that better information exchange is one of the arguments for decentralization one can expect might expect better targeting for own-caste as well. In order to examine this, I estimate equation 1.1 with work days generated for below poverty line (BPL) households and fraction of work days alloted to BPL households. BPL status is determined by local governments and the most recent criteria in 2014 states that the poverty line should be 32 rupees made a day in rural areas. That is, people can be considered below poverty line if they earn less than 32 rupees a day. If we see better targeting, there should be a larger number of own-caste BPL work days. While BPL is an imperfect measure of poverty, it can proxy for those most in need of NREGS jobs.

Table 1.5 shows the triple-difference effects of on BPL targeting. Columns (1)-(3) show the raw number of BPL work days and (4)-(6) fraction of work days going to BPL households. From the first three columns, we see no meaningful effects of alignment in BPL work days. In fact, column (5)'s triple-difference coefficient shows a lower fraction of SC work days going SC BPL households. In other words, even though we see an increase in SC work days from alignment in SC representation as seen in table 1.3, the increase are *not* coming from SC BPL households – households that might need NREGS work the most. This result is inconsistent with the information channel. Column (3)'s coefficient on $LocalSC \times post$ suggest that SC sarpanches lead to decrease in work for non-SC BPL households. However, this appears to be from overall decrease in non-SC work days as column (6) shows that the fraction of non-SC BPL work days actually increase slightly ($p<0.01$) with SC sarpanches. Generally, the effect sizes are rather small, suggesting negligible effects on targeting.

1.8. Conclusion

Decentralization can grant poor minority groups a chance of political representation. However, evidence on whether political representation actually benefits the poor is mixed. Given that decentralized governments rely on the cooperation and delegation of more than one tier of government officials, focusing on representation at one level in isolation can miss an important source heterogeneity.

In this paper, I provide evidence that decentralization can promote the needs of minorities when there is alignment in group across intergovernmental levels. The setting of India is appropriate to study my question as I have detailed data on both the group or caste of representatives and group of households receiving transfers. Additionally, India's caste system that created historical and ongoing inequality created easily identifiable minority groups. The caste reservation system provides exogenous variation in representation as well. Finally, India's rural job guarantee program, NREGS, is the world's largest welfare program and this is an important program in itself. I show that they can be explained through the channels of electoral competition and taste for in-group members.

This paper suggests that the existence of own-group bias can be amplified or negated with a decentralized government structure. Hence, assessment of representation may not be straightforward. In my context, SC households receive 17 more days of work (this corresponds to around 17 percent of average monthly work) at the gram panchayat level monthly when both local and intermediate representatives are SC. Having SC representation only at the local level does not increase transfers to SC households since the *overall* capacity of NREGS distribution decreases with caste misalignment.

Moreover, I explored sources of heterogeneity including taste, electoral motivation, and information. I show that taste for own-caste can be a driving factor behind my results using changes in caste salience through caste protests. Also, by using vote differences in previous election as a proxy for political competition, I see that MLA re-election motives can lead to increased transfers to own-group. This pattern is pronounced for SC households as they are more swingable through government transfers. However, with very low sarapnch re-election prospects without reservation, the rotation of gram panchayat reservation decreases electoral motivation for sarpanches. If re-election motivation also strengthens SC sarpanches' transfer to minority castes at the gram panchayat level, it may be worthwhile to explore increasing re-election possibilities for SC sarpanches. Finally, I do not see evidence that being affected by better information within own-group. It is important to point out that while these results suggest possible mechanisms, I am not able to show exact causes behind my findings.

My findings have policy implications as well. In the context of India, the caste reservation system was instated to promote the status of minority castes. Political posts are reserved independently at each level of government. Yet, according to my findings, without the support of upper level officials, a sarpanch's effort might not be sufficient to provide greater transfers to minority castes may not occur. Thus, for the Indian government, if increasing minority castes' access to resources is a goal, coordination of reservation across different seats may be needed.

There are futures areas of research needed to understand the full story behind my findings. First, it would be useful to have a theoretical model that can deepen the understanding of the channels behind the effects of intergovernmental group alignment. Second, while my findings can speak directly to allocation within local level, the paper's design does not allow me to make causal claims for intermediate representatives' decisions. Supplementing the data with explicit allocation decisions of intermediate representatives can be helpful. Finally, I leave rigorous examination of the causes behind larger transfers to own-group for future work.

1.9. Tables

Table 1.1: Example of Theoretical Reservation Rotation

GP	pop SC	theory reserved 2010	theory reserved 2015
A	120	Y	N
B	110	Y	N
C	90	Y	N
D	80	Y	N
E	75	N	Y
F	70	N	Y
G	60	N	Y
H	58	N	Y
I	50	N	N
J	45	N	N

This table illustrates an example of a gram panchayat reservation process for scheduled castes (SC). In this example, we assume that 40 percent or four out of these ten gram panchayats have to be reserved. Column "pop SC" has scheduled caste population. Theory reserved 2010, 2015 show whether a gram panchayat should be theoretically reserved ("Y") or not ("N") in election years 2010 and 2015, respectively. Note that the gram panchayats have been listed in descending order of SC population. In 2010, we see that the first four are theoretically reserved. In 2015, the next four gram panchayats are reserved, and this pattern continues on with 2020 having the last two (I, J) and first two gram panchayats (A, B) reserved.

Table 1.2: Summary Statistics

	All		Assembly SC		Assembly Non-SC		GP SC		GP Non-SC	
A. Panchayat Statistics										
pop	2649.84	(1678.79)	2520.07	(1524.24)	2675.15	(1706.15)	2340.79	(1322.19)	2691.60	(1717.05)
SC Population	549.25	(445.78)	681.13	(529.26)	523.52	(422.83)	778.45	(471.26)	517.63	(432.71)
Total HH	416.76	(278.78)	394.53	(249.90)	421.09	(283.87)	373.94	(233.92)	422.47	(283.65)
SC HH	108.97	(95.05)	127.03	(108.38)	105.34	(91.70)	141.02	(99.06)	104.55	(93.57)
Non-SC HH	398.85	(284.42)	351.45	(254.04)	408.38	(289.21)	310.14	(239.92)	410.78	(287.65)
Literate Population	1152.26	(836.76)	1123.59	(717.10)	1157.86	(858.05)	1040.71	(663.30)	1167.26	(856.25)
area (sqr-km)	5.73	(8.01)	4.72	(5.05)	5.92	(8.45)	5.23	(7.12)	5.79	(8.12)
unique GP	6126.00	(0.00)	1000.00	(0.00)	5126.00	(0.00)	1438.00	(0.00)	6126.00	(0.00)
B. NREGS Variables										
Total Worked Households	25.21	(66.32)	20.07	(39.06)	26.22	(70.38)	26.08	(63.86)	25.09	(66.66)
Worked HH (non-SC)	18.12	(54.24)	11.94	(26.96)	19.32	(58.01)	16.51	(52.54)	18.34	(54.47)
Worked HH (SC)	7.10	(17.10)	8.12	(16.95)	6.90	(17.12)	9.57	(18.99)	6.75	(16.79)
Total Worked Days	367.46	(1168.49)	283.21	(686.15)	383.89	(1240.26)	384.92	(1126.53)	364.98	(1174.21)
Worked Days (SC)	98.91	(289.67)	109.58	(273.97)	96.83	(292.59)	133.58	(318.89)	94.12	(285.11)
Worked Days (non-SC)	268.55	(954.67)	173.63	(482.64)	287.07	(1020.61)	251.35	(927.41)	270.86	(958.42)
Observations	588096		96000		492096		71037		516756	

Standard deviations in parentheses.

Table 1.3: Triple-Difference Effects on Days Worked

	Days Worked		
	(1)	(2)	(3)
	tot days	SC	non-SC
Inter SC × Local SC × post	37.32*	17.17**	20.15
	(19.69)	(7.38)	(16.58)
Local SC × post	-53.94***	4.31	-58.24***
	(13.70)	(3.60)	(11.82)
Inter SC × post	-25.28	5.96	-31.24
	(29.91)	(10.03)	(24.21)
Observations	588096	588096	588096
R^2	0.441	0.373	0.444
outcome mean	367.46	98.91	268.55
state-time FE	X	X	X
GP FE	X	X	X
unique GP	6126	6126	6126

Standard errors clustered at assembly level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The outcome variables reflect the monthly summation of number of days worked in a given gram panchayat monthly. Note that this is not equivalent to per-household work-days. The first column shows results for all monthly NREGS work-days, and column (2) and (3) are broken down into days worked by only SC households and non-SC households respectively. The first row of coefficients show the triple-difference effects. All estimates include state-time fixed effects and gram panchayat fixed effects. I report outcome variable means and number of unique gram panchayats as well. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.4: Effects of Political Competition

	Work Days		
	(1)	(2)	(3)
	tot days	SC	non-SC
diff vote × Inter SC × Local SC × post	-1.875	-1.362**	-0.512
	(2.757)	(0.650)	(2.445)
Observations	477,748	477,748	477,748
R^2	0.427	0.354	0.432
outcome mean	308.959	86.066	222.893
state-time FE	Yes	Yes	Yes
GP FE	Yes	Yes	Yes
unique GP	5,756	5,756	5,756

Standard errors clustered at assembly level

This table shows heterogeneity effects from electoral competition. "diff vote" is the percentage-point difference between MLA and the runner-up from previous MLA election. The outcome variables are sum of monthly work days created in a gram panchayat where column (1) shows the overall total, and columns (2) and (3) show work days for SC and non-SC households respectively. I report only the quadruple-difference coefficients for brevity. Model includes all triple-difference interactions and *diff vote*, *Inter SC×diff vote*, *Local SC×diff vote*, *Inter SC×Local SC×diff vote*, *diff vote×post*, *Inter SC×diff vote×post*, and *Local SC×diff vote×post*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.5: Triple-Difference Effects on BPL Targeting

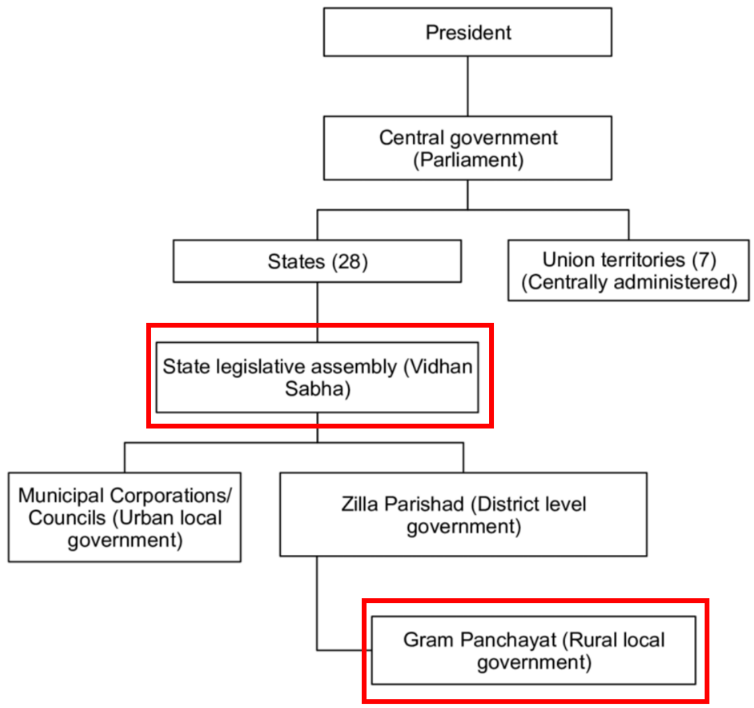
	BPL Work Days			Fraction BPL Work Days		
	(1)	(2)	(3)	(4)	(5)	(6)
	tot days	SC	non-SC	tot days	SC	non-SC
Inter SC × Local SC × post	3.295	1.292	0.909	-0.015**	-0.018*	-0.013
	(2.495)	(1.724)	(1.781)	(0.007)	(0.010)	(0.008)
Local SC × post	-4.632**	-1.496	-3.013**	0.011**	-0.002	0.015***
	(2.098)	(1.045)	(1.248)	(0.005)	(0.005)	(0.005)
Inter SC × post	-1.270	-0.467	-0.235	0.011	0.002	0.012
	(4.030)	(1.354)	(3.178)	(0.016)	(0.016)	(0.016)
Observations	588,096	588,096	588,096	321,599	265,673	310,181
R^2	0.373	0.325	0.348	0.675	0.688	0.618
outcome mean	49.428	18.858	25.703	0.163	0.219	0.132
state-time FE	X	X	X	X	X	X
GP FE	X	X	X	X	X	X
unique GP	6,126	6,126	6,126	5,733	5,602	5,730

Standard errors clustered at assembly level

Columns (1)-(3) outcome variables are the number of work days allocated to below poverty line (BPL) households and columns (4)-(6) show *fraction* of work days going to BPL households. Column (1) shows sum of work-days alloted to BPL households overall, and columns (2) and (3) reflect work days for SC and non-SC BPL households respectively. The number of observations across columns (4)-(6) vary because the fractions are conditional on there being any work-days alloted overall, to SC households, and to non-SC households in order. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.10. Figures

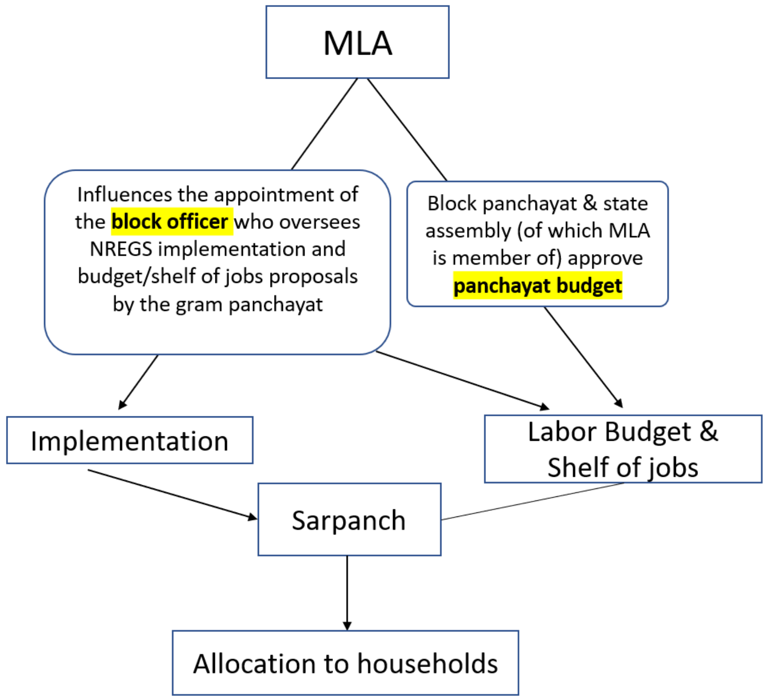
Figure 1.1: Government Structure



Administrative structure of the Indian government. Source: (Human Settlements Division UNESCAP, 2002; Weinstein, 2010)

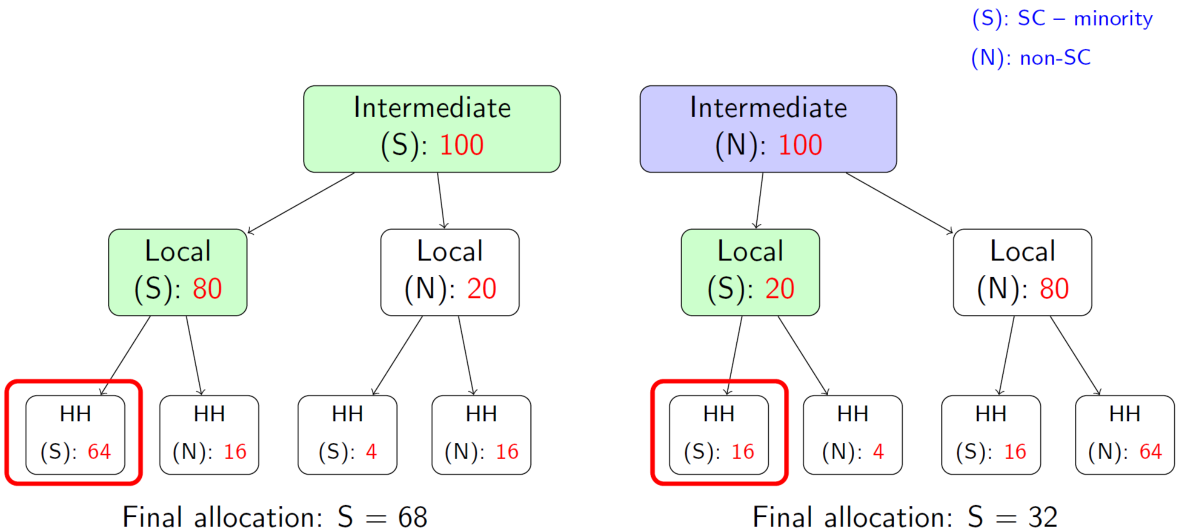
This figure shows a simplified structure of the Indian government. The two positions in interest are the members of legislative assembly (MLA) and the sarpanches. MLAs are part of the state legislative assembly and a sarpanch is the head of the the gram panchayat. The two positions are highlighted with red boxes around them. Note that the state legislative assembly, hence, the MLAs are hierarchically above sarpanches that gover gram panchayats.

Figure 1.2: Roles of MLA and sarpanch



This diagram shows the relationship between MLA and sarpanch for NREGS implementation. While MLAs affect overall capacity of the scheme, the sarpanch can target households in distributing NREGS jobs.

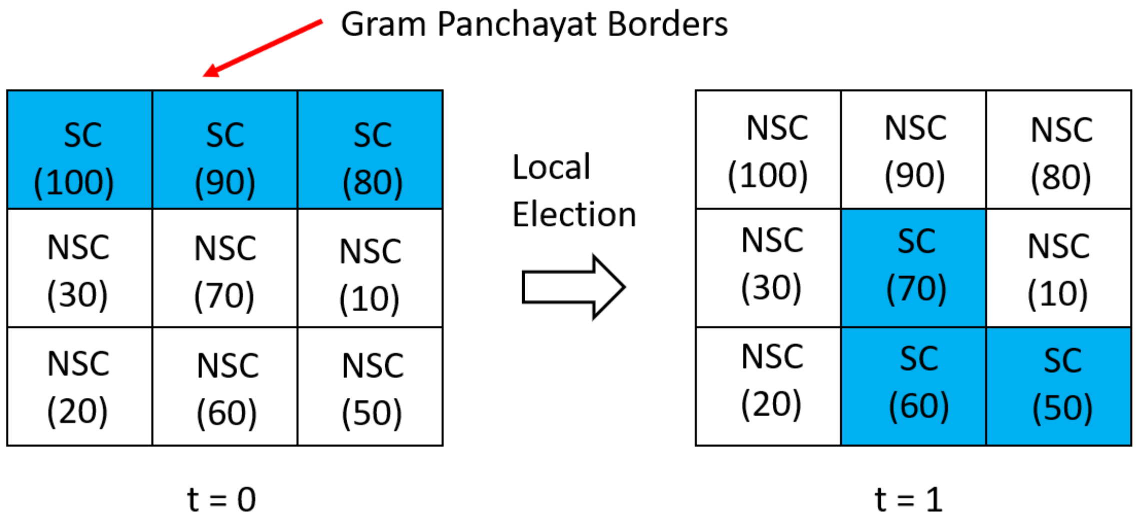
Figure 1.3: Allocation Example



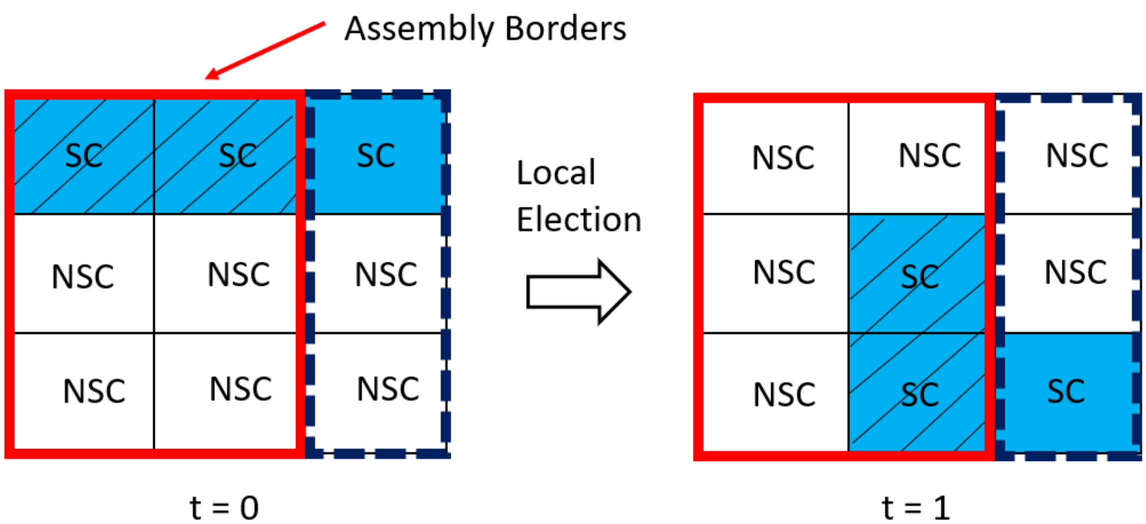
This figure shows how NREGS jobs can be allocated to households in a decentralized government such as that of India. (S) refers to SC and (N) to non-SC. The numbers represent number of jobs to be distributed. "Intermediate" refers to MLAs in this case, and "Local" refers to sarpanches. The last row demonstrates final allocation to households by caste. For the purposes of this figure, we will assume that representatives at both levels distribute more jobs to own-caste at 4-to-1 ratio. The left-hand side of the tree represents allocation process for an SC MLA, who has 100 jobs to allocate. The right-hand side of the tree is when the MLA is non-SC.

Figure 1.4: Reservations

(a) Sarpanch Reservation



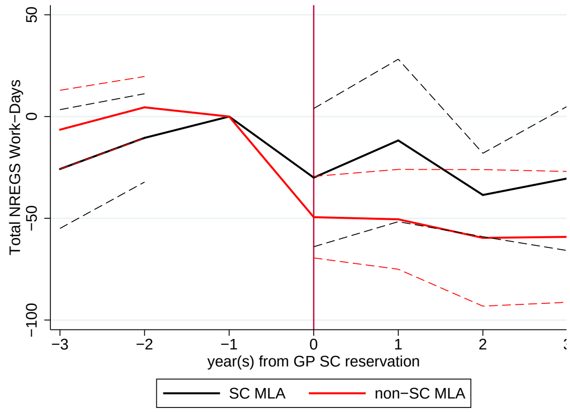
(b) MLA Reservation



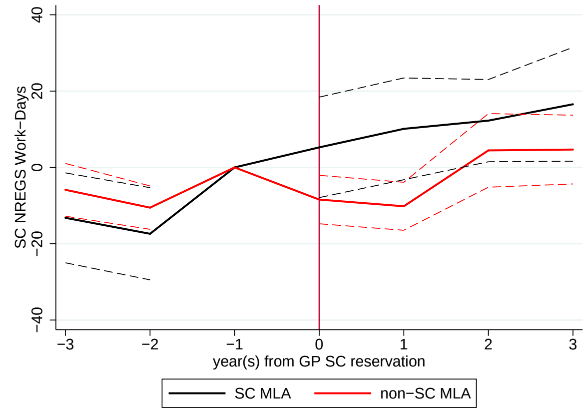
These figures represent the reservation system for gram panchayats and assemblies. Rectangles with "SC" denote SC reserved gram panchayats and "NSC" those that are not reserved for SC. The SC reserved gram panchayats are also colored in blue. In panel (a), the numbers in parentheses denote SC population in each gram panchayat. We see that the selection of gram panchayats reserved changes after a local election (from $t = 0$ to $t = 1$). Panel (b) focuses on assembly reservation. The thick borders represent assembly boundaries and the assembly in solid red is reserved for SC. We see that assembly reservation status does not change overtime. Finally, the shaded rectangles show the gram panchayats that have both SC sarpanch and MLA. The rotating nature of gram panchayat reservation means that over time, intergovernmental alignments change.

Figure 1.5: Event Studies

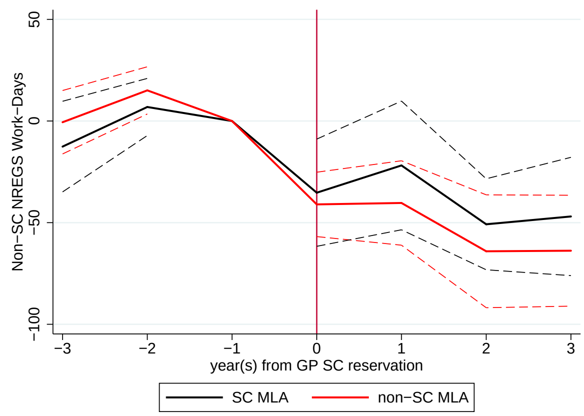
(a) Total Work-Days



(b) SC Work-Days



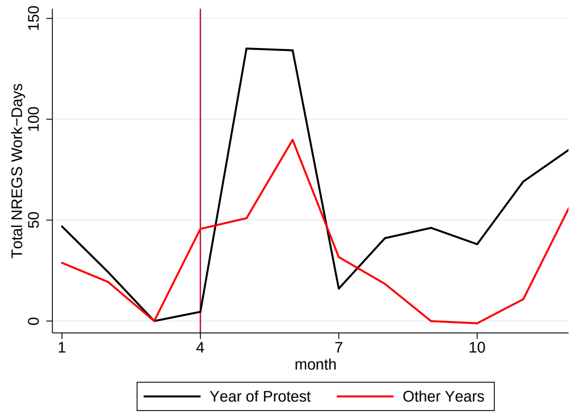
(c) Non-SC Work-Days



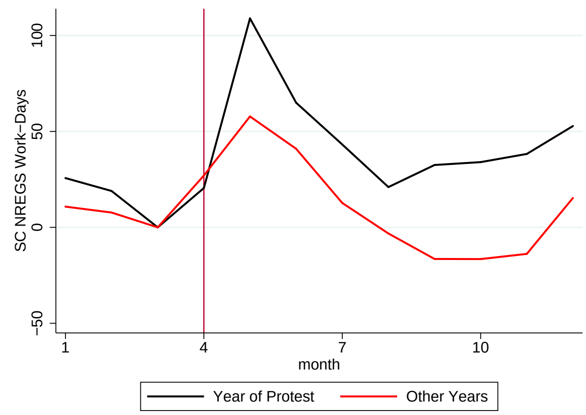
Each panel shows the triple-differences coefficients for each outcome variable. "0" is the year of gram panchayat elections, hence the year of "treatment" for gram panchayats that become reserved for SC. I show three years before and after the election. The base year is the year before sarpanch elections. The black solid lines show effects of SC reservation of gram panchayats for those with SC MLAs. The black dotted lines show the 90% confidence intervals. The red lines show effects of SC gram panchayat reservation for areas with non-SC MLAs and the red dotted lines correspond to the coefficients' 90% confidence intervals. The triple-difference coefficients correspond to the difference of these two lines. In panel (a), I show results for sum of work days created. In panel (b), I show event study results for SC household work-days. We similarly see parallel trends before election. Finally panel (c) shows results for non-SC work-days.

Figure 1.6: Effects of Caste Salience

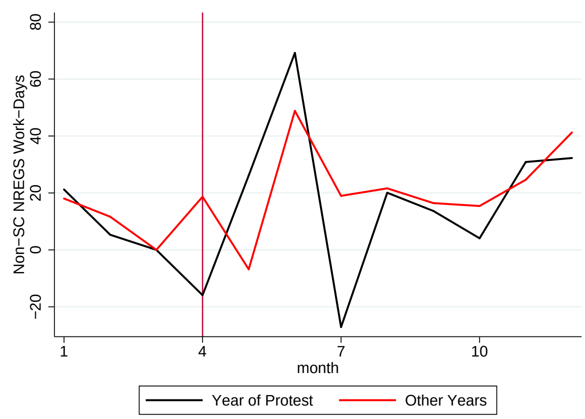
(a) Total Work-Days



(b) SC Work-Days



(c) Non-SC Work-Days



The graphs show effects of caste alignment right before and after protests in 2018, and compare the effects with those of other non-protest years. Panel (a) shows event study results for total work-days generated, (b) SC work-days, and (c) non-SC work-days. The black lines correspond to coefficients for protest year (2018) and the red lines are for non-protest years. All coefficients are in relation to March of each year as the protests happened in April.

CHAPTER 2 : Does Local Government Structure Matter? Investigation Through India

2.1. Introduction

There are many initiatives and grants that target improvement of specific public goods. For example, Modi is launching City Gas Projects across 129 districts to improve availability of clean cooking fuel or Piped Natural Gas for consumers [1]. In Indonesia, there was the Kecamatan Development Project that (KDP) – a government project funded through the World Bank that annually financed projects in villages, usually infrastructure projects. Naturally, much attention is focused on evaluating the efficacy of these programs and potential pitfalls implementation (e.g. corruption in Olken (2007) for KDP's case). However, what is not often considered is the role, if any, of local government structure in effectively implementing these programs.

The question of whether local government structure influences policy implementation has been an ongoing debate with little systematic research (Hughes et al. (1991); Benton (2003b)[2]). If local government structure matters, policy makers should take into consideration how the government structure interacts with future policies and whether the current structure is the best for the nation. In this paper, I address this question of whether local government structure affects public goods provision and if so, how. In order to do this, I exploit the distinct nature of rural and urban local governments in India.

India is suitable to answer this question because of the vastly different structures between rural and urban local governments. The rural and local governments are the smallest self governing units in India and are the building blocks of the Indian democracy. The obligatory

[1] https://energy.economictimes.indiatimes.com/news/oil-and-gas/pm-modi-to-inaugurate-work-on-cgd-projects-boosting-gas-supply-for-half-the-countrys-population/66706395

[2] For a list of papers that contribute to this debate please refer to the literature in this paper.

presence and roles of these local governments were constituionalized after the implementation of 73rd (for rural) and 74th (fur urban) amendments in 1992 and 1993 respectively. I use the urban and rural local government designation for variation in governance structure. Each rural local government is composed of villages while each urban local government is composed of wards. In general, while the rural local government is more informal and less structured, the urban local government has better defined roles. Rural local governments have a hierarchical three-tier system at the settlement, sub-district, and district levels, from lowest to highest in hierarchy. I focus on the settlement level rural local government throughout the paper as it is a comparable level of local government to the urban local government. On the other hand, for urban local governments there is no hierarchy. Given the hierarchical nature, communication between local officials and the state government is harder for settlement level rural local government officials.

Also, the suggested functions differ, with rural local governments' functions being more agriculture focused and urban local governments' functions addressing more urban issues such as, planning and slum improvement. Importantly, while state governments can allow both types of governments the authority to collect taxes, urban local governments are more likely to collect taxes and impose stricter regulations and fees for businesses and constituents.

The decision of which settlement to make rural or urban is not arbitrary. While the decision is meant to rely on objective measures of urbanization, often times politics and path-dependence are determining factors as well. Throughout the paper, I call areas with urban governments "admin urban" and rural local governments "admin rural."

One of the main concerns with using the rural and urban designation is that I am simply looking at the effects of urbanization on public goods provision. To isolate the effects of government structure on local public goods provision, first, I employ a control strategy using satellite data to measure extent of urbanization. Daylight satellite data's uses in economics have been increasing, mainly to identify urbanization (Dingel et al. (2019); Baragwanath Vogel et al. (2018)). Moreover, I flexibly control for observables such as, population, density and socioeconomic variables such as, fraction literature within a settlement. Finally, in order to allow for selection on unobservable characteristics at the district level I include district fixed effects. I find that despite the inclusion of these controls and fixed effects, urban local governments give better access to local public goods across multiple variables and independent of the source of satellite data I use to measure urbanization. I also provide results for placebo tests that show that the government structure does not directly impact access to *private* goods. While I do not provide results here, matching strategy also shows consistent findings.

Next I turn to mechanisms behind these results. I claim that financial decentralization is a channel for better access in public goods for admin urban areas. I use West Bengal's local government level revenue data to show that admin urban areas have a higher level of reliance on own-source revenue as opposed to central and state government transfers. Consistent with Martinez (2018) and Gadenne (2017), I find that higher levels of own-source reliance is associated with better access to public goods.

Finally, I provide heterogeneity tests. I find that compared to an admin urban area that does not neighbor other admin urban settlements, an admin urban area with neighboring admin urban areas experience less of an increase in public goods access. I argue that this result is due to spillover effects. That is, admin urban areas that neighbor other admin urban areas were already enjoying spillover effects even prior to becoming admin urban themselves. As a result, the benefit of becoming admin urban is less dramatic. I support this argument by showing that settlements that neighbor admin urban areas are less likely to become admin urban possibly because the citizens already access admin amenities due to spillovers with lower taxes, thereby, being resistant to changing their government status.

I contribute to the literature examining whether local government structure affects public service provision in several ways. As mentioned before, there is little systematic and empirical investigation in this area. In addition, most of these papers look at developed countries. I complement existing literature by filling in the gap of the lack of research on governance structure in developing countries and employing empirical methods to provide a systematic within-country investigation. More recent papers started to speak to developing countries' local government structure. Closely related is Hiranandani (2018). Like this paper, the author investigates the differences in rural and urban governments' development indicators in India and finds better levels of "high spillover" development indicators, which include road length, fire service, and drainage, for urban governments. I further this research by utilizing the entire sample of India rather than limiting my sample to urban areas and effectively controlling for urbanization through satellite data. The World Bank has a report (GSURR and Frontier (2015)) that also investigates the role of urban government but does not find any effect on public goods access. However, this report mainly looks at a small number of cases through matching, without giving a comprehensive overview of India. Importantly, unlike the recent literature, I explore mechanisms through which governance can matter.

This paper also speaks to the financial decentralization literature by exploring decentralization channels. I am able to speak to the effects of financial decentralization using unique data from West Bengal, bolstering the findings of Martinez (2018) and Gadenne (2017). While the authors mainly discuss education, the variety of my outcome variables are able to show that the effects of greater financial decentralization applies to many aspects of public services outside of education. While it is not the focus of this paper, I also innovate by finding a novel usage of satellite data as a control for urbanization.

The rest of the paper proceeds as follows: Section 2.2 provides background on India's local governance structure and reasons for why it is an attractive setting for this study. Section 2.3 presents the estimation framework for the effect of admin urban and Section 2.4 shows results of the empirical exercises Section 2.5 provides evidence on mechanisms and Section 2.6 heterogeneity effects. Section 2.7 concludes.

2.2. Setting and Background

The 73rd and 74th amendments that were put into effect in 1992 and 1993 mark the constitutional beginning of decentralization and self-governance in India. Prior to the amendments, local governance was entirely dependent on the states. As a result, local governance varied widely across states. The amendments detail that every settlement needs to be represented by panchayats (for rural areas) or municipalities (for urban areas), which are the smallest level of self-governance. Moreover, through these amendments, the distinction between rural and urban local governments became clearer. I will call areas with an urban local government "admin urban" and areas with a rural local government "admin rural" throughout this paper.

2.2.1. Difference between urban/rural local governments

Broadly, urban local governments have more autonomy from the state governments and are structurally more well-defined than rural local governments. The rural local government has a hierarchical three-tier structure with village (gram panchayats), block (or sub-district), and district governments in order of hierarchy collectively known as the Panchayat Raj Institutions. Given this structure, often times the lower level local government has to get clearance from the upper level before making decisions. On the other hand, urban local governments have a horizontal structure. There are three different types of urban local governments but they do not have a hierarchical relationship. In order of size, there are nagar panchayats, municipalities, and municipal corporations. An implication of this structural difference is greater provisional autonomy for urban local governments.

A non-structural difference between urban and rural local governments come from the support from states. In general, many states have not transferred the required staff after devolution of functions. Also, many government officers are not willing to work under the administrative control of elected rural local officials. That is, while in theory, rural governments are self-governing, the state government do not give the sufficient support to enable self-governance (Satyanarayana (2015)). On the other hand, the constitution states that legislature of a state may, by law, provide members of persons having special knowledge or experience in Municipal administration or urban areas.

Both types of local governments may technically be given authority to raise their own revenue through taxes and fees. However, both, but especially the rural governments, primarily rely on grants-in-aid from state/central government. For instance, in 1999-2000 0.04% of GDP was raised by rural local governments whereas 0.5% of GDP was raised by urban local governments in 1999-2000 (Govinda Rao (2003)). Property taxes are the main source of revenue from their tax revenue. I will discuss this in more detail in section 2.5.1.

2.2.2. Admin urban/rural designation and transition

According to the amendment, the Governor may designate an area as transitional, or nagar panchayat (the smallest level of urban local government), "having regard to the population of the area, the density of the population therein, the revenue generated for local administration, the percentage of employment in non-agricultural activities, the economic importance or such other factors as he may deem fit." While the amendment does lay out these criteria to be considered, they are neither concrete nor binding. Instead, concrete criteria depend on the state, although not all states have these. Yet, even states with formal criteria, most states do not actually follow through with their official transition criteria. I consulted a source who has worked through the transition of an area with a rural government to an urban government. From his experience, the transition was largely politically motivated in that politicians initiated the transition for potential personal gains with little to no consideration of the official criteria for transition.

What are the motivations behind politicians wanting (or not wanting) to push for rural to urban transition? This depends on the stakes of the politician. On one hand, some politicians are fearful of giving up their fiefdom if their village gets absorbed into a larger town or villages combine to become a town. In contrast, anecdotally, politicians who own a lot of land in a rural settlement want to change the settlement's status in hopes of land value appreciation. Constituents also have a stake in the transition, mainly through the increased taxes and fees. Those who support the transition do so in the hopes of better service provision. However, some fear increase in taxation and loss of rural-targeted welfare programs. Similarly for businesses, while there are hopes for better connectivity and services there is also the fear of stricter regulations and increase in taxes and fees.

There can be potential confusion regarding urban areas because India has two separate categories of "urban" settlements. Conventionally, the two categories are known as (1) statutory towns and (2) census towns. Statutory towns are what I refer to as admin urban areas. Census towns are towns only in the eyes of the Indian census. That is, they are not designated or recognized as urban by the central or state government. Specifically, census towns are "places which satisfied the following criteria: a minimum population of 5,000; at least 75% of the male main working population engaged in non-agricultural pursuits; and a density of population of at least 400 persons per sq km." Although these places show the characteristics and problems of an urban settlement, since the state does not recognize them as a city, they are governed as admin rural.

2.2.3. Mismatch of De Jure and De Facto Urban Designation

Figure 2.2 is a satellite image of Jhalda in West Bengal. At first glance it looks very rural with little development. Surprisingly, despite the looks of it, Jhalda is a municipality or admin urban with an urban local government. In Figure 2.3 we have Panchpar, also in West Bengal. Compared to Jhalda, we see a lot more development. Panchpara, however, is actually a village with a rural government. These settlements are not one-off examples and I will provide a more systematic overview of extent and pattern of these "mismatches" in section 2.3.1.2. What are the effects of the mismatches? If local governance structure matters for provision of public goods, the mismatch can potentially be causing inefficiencies in allocation. India not only have two very different local government structures, but also these governance structures might be incorrectly assigned, making it essential to understand the roll of local governance, if any.

2.3. Empirical Strategy

The goal is to estimate the causal effect of different local governmental structures on public goods provision. I use census data from India for years 2001 and 2011 to test the hypothesis that local governmental structure has an effect on public goods provision. I exploit the fact that India's local governments are largely divided into rural and urban local governments with vastly different structures. Given that the type of local government is not randomly distributed across settlements, I cannot simply compare the level of public goods access between admin urban and admin rural areas. In the following subsections, I go over the data and discuss controls strategy and fixed effects.

2.3.1. Data

2.3.1.1. Public Goods and Socioeconomic Variables

The Indian census provides basic socioeconomic information about each settlement such as, number of households and population. The census further contains socioeconomic variables, such as, fraction of Scheduled Caste/Tribe (SC/ST), fraction employed, fraction living in dilapidated houses, fraction with mud roof, and so on. The summary of these variables are in Table 2.3. The results use only 2011 data and are divided into type of settlement according to the 2011 census. The first two columns have admin rural areas. I however, did split the admin rural areas into villages and census towns (CT). Admin urban areas are divided into four categories, where NP stands for nagar panchayats, and are the smallest level of admin urban areas. The "other" category is mostly made up with cantonment boards. One pattern that stands out is the overwhelming number of admin rural areas. Administratively, India is mostly consisted of rural settlements. Moreover, we see that villages are much smaller in population and area compared to any other type of settlement. Census towns, while technically admin rural, are much larger than villages that are both admin and de jure rural. When looking at nagar panchayats, municipalities, and municipal corporations, the size, in terms of both population and area look as expected with nagar panchayats being the smallest and municipal corporations being the largest with municipalities in the middle. On average, villages have higher fractions of scheduled cast and tribes compared to admin urban areas. As one might expect, more people in villages work in agriculture or cultivation, both when looking at overall population or the male population. While municipalities and municipal corporations have very low fraction of men working in agriculture (5.4% and 1.4% respectively), nagar panchayats clearly look less urbanized with 11.6% of their male population employed in agriculture or cultivation. The final four variables give us a glimpse of the economic status of the households in India. These variables suggest that villages are on average worse off compared to admin urban areas. Interestingly, fraction of houses with mud roofs and grass or mud walls are higher in nagar panchayats compared to census towns.

The outcome variables are measures of public goods allocation. This data also comes from India's census rounds 2001 and 2011 and includes variables such as fraction of households with access to tap water, electricity, LPG/PNG gas, and drainage system within a village or municipality. All the data is at the settlement level. The caveat with these variables is that we cannot be sure that the services are purely from the government. It is entirely possible that citizens get their services privately. Potentially, wealthier citizens have more private supplies of services such as, treated tap water. Given that, on average, cities are richer, this biases the effect of having an urban government on public goods access upwards. Moreover, the data does not speak to the quality of the public goods. Summary statistics of the outcome variables used in the analyses are in Table 2.4, which only contains 2011. Again, I breakdown the averages by settlement type. From Table 2.4, we see that overall, villages do have the worst level of access to public goods compared to other types of settlements. An exception is the number of elementary schools per 1,000 people. This is likely due to the small population of villages. Villages also have higher fraction of households with untreated tap water compared to municipal corporations, but this is because most households there (around 67%) have access to *treated* tap water. From these two tables, we see that admin rural areas are on average, smaller and poorer with worse public service access compared to admin urban areas.

2.3.1.2. Urbanization

I use three different methods to identify urbanized areas using satellite and population data. I identify urbanized areas in order to control for the degree of urbanization when comparing admin urban and rural areas. The idea is that controlling for the level of urbanization, socioeconomic variables, and fixed effects, the designation of admin urban can be as good as random.

For the first method I use MODIS data as in Baragwanath Vogel et al. (2018). I use 2001 daytime satellite imagery to look at the builtup landcover constructed by Channan et al. (2014). The MODIS data is categorical – that is each pixel is either urban or one of the other categories such as, water, mixed forest, and so on. One of the categories is "urban and built-up" and I consider areas covered by pixels of this classification to be "satellite urban." However, the satellite data does not follow any administrative boundary. Instead, it consists of pixels of the size of 500 meter by 500 meter. In order to determine settlements that are considered urban in the satellite data, I overlay the satellite image with the settlement-level administrative boundary map of India. I classify a settlement as "satellite urban" if maximum fraction of the area of a settlement is designated as "urban and built-up" by the satellite data. The result of this classification is in Table **??**'s first column. Alarmingly, most of the settlements determined as "urban" by MODIS data is actually administratively rural.

Using the same data, I also create a continuous variable of urbanization by calculating the fraction of area classified as "urban and built-up" within a settlement.

For the third approach, I use Human Built-up And Settlement Extent (HBASE) data and follow the method of Dingel et al. (2019). The preferred data is MODIS because 2001 data available. Given that I use 2011 outcome variables, using 2001 urbanization controls help me avoid the "bad control" problem. HBASE data unfortunately starts from 2010. However, unlike MODIS data, each pixel in the HBASE data has a continuous number between 0-100 that measures the probability of being builtup. Again, HBASE is pixel data with 500 meter by 500 meter dimension that does not follow administrative boundaries. Figure 2.1 demonstrates the process I use to designate a settlement "satellite urban". The first gridded image in Figure 2.1 represents the satellite image, where the number in each square, called grid code, signifies the imperviousness level, i.e. the level of human builtup. From this, I group together contiguous grids that are over a certain threshold (in this case, the threshold is 50). I then overlay the satellite image with the administrative boundaries (image on the top-right in this figure). Let's call the administrative boundaries overlapping with the contiguous polygon "candidate" boundaries. As it can be seen from the bottom image, area B is completely within the contiguous polygon and hence is a "candidate". Boundaries A and C overlap with both the grid code $>$ 50 contiguous polygon and the rest. Since the contiguous polygon does take up the most area for these two boundaries, we include settlements A and C as candidates. Now we have contiguous *settlements* consisting of areas A, B, and C. Finally, we add up all the contiguous candidates' population and see if this exceeds 50,000. If so, I designate A, B, and C as satellite urban. The result of following this process is in **??**, second column. Again, we see that most of the identified satellite urban areas are administratively rural. If we can trust the satellite data, this is clear evidence of mismatch in government type as described in Section 2.2.3.

Now, I provide more information about the satellite urban areas that are identified using the above described methods. Specifically, I investigate whether these satellite urban areas are simply peripheries of admin urban areas or newly developed clusters removed from existing admin urban areas. Table 2.1 shows the breakdown of satellite urban areas by dataset and whether they neighbor admin urban areas. From both datasets, we see that about half of the satellite urban areas are neighboring admin urban settlements. While there are many satellite urban settlements that neighbor admin urban areas, it does appear that there is unrecognized urbanization happening away from existing admin urban areas.

Table 2.1: Breakdown of Satellite Urban

	MODIS			HBASE		
	neighboring admin urban					
	No	Yes	Total	No	Yes	Total
admin rural	1,178	1,378	2,556	1,498	1,472	2,970
admin urban	214	178	392	308	205	513
total	1,392	1,556	2,948	1,806	1,677	3,483

2.3.2. Identification

Again, the question at hand is whether local government structure matters for local goods provision. In order to answer this question, I exploit the fact that India's local urban and rural governments have large structural differences. The following is the baseline estimating equation:

$$Y_{it} = \beta_0 + \beta_1 admin\_urban_{it} + X_{it-10} + \gamma + \epsilon_{it} \tag{2.1}$$

The outcome variable Y_{it} is a measure for access to public goods, such as fraction of households with access to treated tap water in settlement i in year t. The main regressor of interest is $admin\_urban_{it}$. $admin\_urban_{it} = 1$ if settlement i is administratively urban in year t and 0 otherwise. A key limitation of the decadal census is that we do not know when the transition to admin urban happened. Hence, $admin\_urban_{it} = 1$ means that settlement i became admin urban anytime before t. Since I do not know how long a settlement has been admin urban, I am not able to measure the heterogeneity that might come from shorter or longer exposure to being admin urban. On the other hand, the outcome variables Y_{it} and controls X_{it-10} are more of a snapshot of the circumstances of the time period of when the census survey was conducted. X_{it-10} are lagged control variables – this includes logged population, logged area, density, fraction SC/ST, fraction of workforce working in agriculture, fraction literate, distance to district headquarters and an indicator variable for being a cantonment board. It is important to control for these observables since, as we saw from table 2.3, admin urban areas are larger, denser, and likely richer. Therefore, it is reasonable to expect that there is better public service provision in admin urban areas independent of the local government type. Finally, γ are district fixed effects, given that policies and decisions are often made at the district level. Specification (2.1) identifies the causal effect of $admin\_urban_i$ if selection into $admin\_urban_i$ is more or less random conditional on observables X_{it-10} and district level unobservables. While I do include a battery of controls that account for urbanization I cannot capture all of it through observables. I address this issue using satellite data that captures urbanization.

A complication in using more than one wave of the Indian census is the concordance across years. India's boundaries are continuously changing, and especially, when it comes to transitioning from admin rural to urban, boundary changes are not uncommon. Hence, it is important to take these boundary changes into account when using multiple census years. I follow Perlman (2014) and unify the data to follow 2011 boundaries.

2.3.3. Satellite data and fixed effects

One of the major concerns of simply using equation (2.1) is the effects of unobserved factors that are related to urbanization and access to public goods within the district level. While variables such as, population, density, and socioeconomic variables do explain urbanization, they cannot fully account for urbanization. Therefore, I identify urbanized settlements *directly* by using methods and data delineated in section 2.3.1.2. I call areas identified as urban (rural) via satellite data "satellite urban (rural)." I divide the sample using this empirical distinction and estimate equation (2.1). The idea is that within a sample of satellite urban or rural and controlling for additional observables and district fixed effects, the admin urban designation is as good as random. Alternatively, using the continuous measure of fraction satellite urban, I directly control for the level of urbanization by including a linear "fraction urban" term in equation (2.1). A lingering issue with this identification strategy is that there are still concerns of unobservables that are related to the admin urban status public goods provision, such as political connections. Such unobservables can correlate with both the $admin\_urban_{it}$ status and Y_{it}. I will use a panel framework to address this issue.

2.3.4. Controls

It is worth going over the controls I use other than measures of urbanization through satellite data given they play a central role in restoring randomness in admin urban designation. The obvious ones are the population, density, and area controls. Since we see a positive correlation between these factors and public goods access, it is important to control for these to make sure our admin urban variable isn't simply picking up the effects of larger settlements. I also control for the fraction of scheduled caste (SC) and scheduled tribe (ST). Fraction SC/ST can control for some socioeconomic differences across settlements. They also, to an extent, reflect caste diversity within settlements, and social diversity is often connected to public goods access and economic performance (Alesina and La Ferrara (2004), Miguel and Gugerty (2005)). Fraction literate also controls socioeconomic differences. I do not have country-wide income or expenditure data for India, so I use proxies like fraction literature instead. I also control for fraction of people working in agriculture or cultivation. This should be able to further control for level of urbanization. I include all of these variables' quadratic forms as well. As per Asher et al. (2018) I include distance to district headquarters. The authors find that villages more remote from their administration have poorer access to public infrastructure and service such as roads, schools, health centers, and irrigation. Finally, I include a variable for a settlement being a cantonment board as they are notified under the Cantonments Act of 2006 which replaced the Cantonments Act of 1924.

2.4. Results

Here, I present the results of my empirical exercises. I first go over the results from using satellite data and fixed effects then go over the panel results. I consistently find statistically significant and positive effects of being admin urban on public goods access. For all analyses, I drop settlements in the bottom five percentile of 2001 population. The reason being, these settlements are so small that it is close to impossible to find admin urban areas that are comparable, making the analyses potentially biased upwards, inflating the positive effects of urban local governments.

2.4.1. Satellite control and fixed effects

First are the results from the satellite controls and fixed effects strategy. Due to data limitations, the analyses only contain 2011 outcome variables. Tables 2.5 and 2.6 show results from direct urbanization control with a fraction urbanization covariate measured from the fraction of settlement area classified as urban from the MODIS data. Table 2.5 uses the entire sample. Qualitatively, we see that being admin urban positively impacts public goods provision. We also see that the being more "urban" according to the satellite data is positively correlated to better provision of public goods. Table 2.6 excludes all settlements with no satellite urban areas. The results are qualitatively the same as when using the whole sample. We do see, however, that most of the settlements are not satellite urban areas. Tables A.2.1 and A.2.2 use HBASE data and tables 2.7 and 2.8, MODIS data urban designation. The samples are further divided into satellite urban and rural. The results across samples and datasets are consistent. Controlling for level of urbanization, there is a qualitatively positive and statistically significant effect of being admin urban across all outcome variables. The outcome variables, except for index, are the fraction of households with access to the particular good.

The interpretation of column (1) of Table A.2.1 is as follows: within satellite urban sample after controls and district level fixed effects, a settlement that is admin urban, on average, has 14.7 percentage point greater provision of treated tap water across households. I created the outcome variable "index" that is the average fraction of amenities a household has access to within a settlement from amenities, (1) treated tap water (2) access to light (3) access to light via electricity (4) waste water drainage and (5) LPG/PNG gas for kitchen. For example if a household has LPG/PNG gas and treated tap water that house will have index of 2/5. The index enables me to get a cohesive picture of the effect of being admin urban on public goods access with significantly less noise compared to the other outcome variables. A key aspect both Martinez (2018) and Gadenne (2017) look at is education. Yet, for admin urban local governments, schools are actually not an obligatory responsibility, so I do not include education variables here. I did, however, estiamte the effects of admin urban on number of government primary schools, and the results were not consistently statistically significant, as expected.

Now, I present graphical evidence. The graphs below use just the settlements with urban area > 0. The figures to have level of urbanization on the x-axis. I created the "urban bins" using a linear combination of fraction of area urban using MODIS data, population, and density. For each bin, I estimate equation (2.1) separately. The coefficient on $admin\_urban$ and 95% confidence intervals are reported in the graphs on the left side for each outcome variable. There are two main observations to be made here. One is that there does not seem to be a systematic patten between magnitude of the coefficients and level of urbanization. The other is that across all level of urbanization the effects of being admin urban are statistically significant and qualitatively significant. The right sides of the graphs are the predicted outcomes for admin rural and admin urban separately. For the most part, provision of public goods seem to improve with greater level of urbanization for both admin urban and rural settlements. Admin urban and rural settlements actually look rather parallel in their trends.

2.4.2. Placebo Test

There can be lingering concerns that the effects of admin urban we saw from section 2.4.1 is simply picking up the effects of admin urban areas being better off. If that were the case, we should expect to see positive effects being admin urban on private services as well. However, if I am successfully isolating the effects of governance structure, we should not expect to see effects of being admin urban on private alternatives to public services. The census provides numbers for private schools for both rural and urban settlements, so I repeat the same empirical exercise as section 2.4.1. For the sample of admin rural areas, there is a binary variable for whether there are private bus services. In addition, for the sample, of census towns and admin urban areas, there is a variable for number of banks by settlement. While these two variables do not cover the whole sample, I do include them in the analyses and control for whether or not the settlement is satellite urban.

For both Tables **??** and **??**, columns (1)-(4) use the satellite urban sample, while columns (6)-(9) use satellite rural. All outcome variables except for "priv bus" signify the number of private schools/banks per 1,000 people. We see that overall admin urban does not seem to be have a systematic effect on private services. None of the coefficients, across sample and data, are distinguishable from zero, as expected.

2.5. Mechanism

From the empirical exercises, I show qualitatively positive and statistically significant effects of a settlement being admin urban, thereby demonstrating the importance of local governmental structure on public goods provision. In this section, I explore the mechanism through which this can be possible. I first discuss the mechanism of financial decentralization. I measure financial decentralization using fraction of local own-source revenue as opposed to transfers from the state and/or central government.

2.5.1. Financial Decentralization

A lot of the literature discussing the effects of variations in local governments' revenue on public goods provision find significant leakage and lack of variation in resources and public goods outcomes. However, these papers (for example, Reinikka and Svensson (2004), Reinikka and Svensson (2006), and Olken (2007)) focus mainly on revenue from transfers. However, while there isn't a large literature on it yet, when we focus on *own-source* revenue, the results differ. Both Martinez (2018) and Gadenne (2017) find that increase in own-source revenue, specifically tax-revenue leads to improvements in public services. In particular Martinez (2018) finds that increases in tax-revenue leads to improvements in education, health, and water quality while Gadenne (2017) finds improvements in both the quality and quantity of education. Importantly Gadenne (2017) shows that improvement in capacity of raising own-source revenue can have direct consequences on provision of public services. In my context, I argue that the change from admin rural to admin urban status increases the capacity to better raise own-source revenue, and the increased capacity manifests itself through larger fraction of own-source revenue in admin urban areas.

2.5.1.1. Setting and Data

While the results so far have been for India as a whole, due to data limitations, I explore West Bengal in particular. West Bengal published detailed local revenue and budgetary data through its fourth state finance commission report. The data spans from 2007-2008 to

2012-2013 and goes down to the local government level i.e. gram panchayat level for admin rural areas and municipal level for admin urban areas. For both admin rural and urban areas, variables for total revenue, transfers, non-tax revenue, tax revenue, and expenditures on wages for public servants and civic services are available. Table 2.10 provides a per-capita breakdown of these variables by admin rural, urban, and overall. The numbers are in 100,000 rupees and averaged across the years. In general, we see that admin urban areas have greater revenue across different sources of revenue. They spend less in per capita on civic services. This latter result may be because admin urban areas are able to take advantage of economies of scale. In dollars, the per-capita tax amounts to about \$0.15 a year for admin rural areas and \$149 a year for admin urban areas. When limiting the sample to just satellite urban areas as defined with MODIS, the differences in revenue are much smaller across admin rural and urban areas, but the same pattern persists.

For just the admin urban areas, data of the breakdown of transfers are available and are presented in **??**. About half of the transfers are for development programs such as, Jawaharlal Nehru National Urban Renewal Mission (JNNURM), which is focused on capital development. The main aspect to note here is the relatively low fraction of transfer that is untied. Only about 15% of all transfers to admin urban areas are untied. This supports my argument that fraction of own-source revenue reflects financial autonomy.

2.5.1.2. Relationship between admin rural/urban and fraction transfer

In order to test whether financial decentralization is a mechanism, I first have to show the relationship between admin rural/urban status and degree of financial decentralization. That is, we are interested in:

$$decentralization_{it} = \alpha_0 + \alpha_1 admin\_urban_{it} + X_{it-10} + \gamma + \epsilon_i \tag{2.2}$$

With the budget data we can estimate the following:

$$frac\_ownsource_i = \alpha_0 + \alpha_1 admin\_urban_{it} + +X_{it-10} + \gamma + \epsilon_i \tag{2.3}$$

Here, I am proxying level of decentralization using fraction of the local government's revenue that comes from own-source as opposed to central or state transfers. Again I control for logged population, logged area, density, fraction SC/ST, fraction of workforce working in agriculture, fraction literate and all of these variables' quadratic forms, and distance to district headquarters. Own-source revenue is the sum of tax and non-tax revenues. I argue that fraction of own-source revenue is a good measure of financial decentralization as local governments have more authority over how to spend own-source revenue compared to transfers that are mostly tied to specific purposes. Moreover, it reflects local governments' financial autonomy and capacity to collect their own revenue.

The results in Table **??** show results for equation (2.3). I exclude information for financial year 2012-2013 since I only have admin urban information up until 2011. The first two columns in the table show the main outcome variable of interest – fraction own-source revenue. The fraction of own-source revenue is statistically significantly larger in admin urban areas compared to admin rural areas in the satellite rural sample. Specifically, column (2) shows us that within satellite rural areas, after controlling for socioeconomic variables and district fixed effects, being admin urban is associated with approximately 11-12 percentage-point higher own-source revenue compared to admin rural areas. Column (1), does show a negative relationship between admin urban and fraction own-source revenue for the satellite urban sample, but the standard errors are rather large. This result is interesting as settlements that are both admin and satellite urban seem to be already collecting more own source revenue with or without the presence of the urban government. This might suggest that greater financial decentralization is not a channel for satellite urban areas. However, there also could be increased financial independence that are not captured by fraction of own-source revenue.

The rest of the columns breaks down the own-source revenue. Columns (3)-(4) show the relationship between admin urban and fraction of tax and (5)-(6) fraction of non-tax revenue. Unexpectedly, fraction of taxes are actually lower in admin urban areas across both samples. However, this result seems to be driven from the fact that admin urban areas have a much larger fraction of non-tax revenue rather than from the small size of tax collection compared to admin rural areas. Columns (5) and (6) show positive and statistically significant relationship between being admin urban and fraction of non-tax revenue. While column (5) shows a positive sign, again the standard errors are too large to conclude that it is statistically different from zero. This satellite urban sample is lacking in sample size for us to making meaningful conclusions. I plan to add more data from other states in the future.

2.5.1.3. Fraction own-source revenue and outcomes

Now I turn to the direct relationship between fraction of own-source revenue and public goods provision. I estimate the following equation:

$$Y_{it} = \alpha_0 + \alpha_1 frac\_ownsource_{it} + X_{it-10} + \gamma + u_i \tag{2.4}$$

Where Y_i is an outcome variable for service provision. Given that the revenue data is panel data within one census survey period, I collapse years 2007-8 to 2010-11 to create $frac\_ownsource$.

The results are in Tables 2.12 and 2.13. We see a (qualitatively) positive and statistically significant relationship between fraction of own-source revenue and public service provision across both satellite urban and rural samples independent of the satellite data source. All standard errors are clustered at the sub-district level. This suggests a positive correlation between financial decentralization and public service provision as a mechanism. Fraction own-source revenue seems to affect satellite rural areas more than satellite urban areas.

Consistent results are shown when using HBASE as well (Tables A.2.5) and refrfRuralHBASE)

2.6. Heterogeneous Effects

In this section, I explore heterogeneous effects of being admin urban. In particular, I investigate whether being a neighbor to another admin urban area affects the impact of being admin urban. This particular heterogeneity is of interest given that we saw from Table 2.1 about half of all satellite urban areas neighbor admin urban areas. Moreover, considering neighboring admin urban areas will help us understand spillover effects, if any. In order to investigate this, I estiamte the following:

$$Y_{it} = \beta_0 + \beta_1 admin\_urban_{it} + \beta_2 admin\_urban_{it} \times urban\_nbr_{it} + \\ X_{it-10} \cdot urban\_nbr_{it} + \gamma \cdot urban\_nbr_{it} + \epsilon_{it} \quad (2.5)$$

Here, I include interaction terms with $urban_n br_{it}$, which equals 1 if a settlement i neighbors an admin urban area. The coefficient of interest is β_2 – it gives us the effect of having an admin urban neighbor given that i is admin urban. Tables 2.14 and A.2.7 show results for the satellite urban samples. We see that given that an area is admin urban, compared to admin areas that do not neighbor another admin area, admin areas neighboring another admin area are less likely to have light through electricity and more likely to use kerosene for light. The HBASE sample also shows that admin urban areas neighboring other admin areas have less access to LPG/PNG gas. One exception to the general negative effects of having a neighboring admin urban area is drainage. The satellite rural sample (Tables 2.15 and A.2.8) show the same pattern but with more variables showing statistically significant and negative coefficients, including open drainage and index.

At first, this may be a puzzling result. However, it really shows that most likely, settlements neighboring admin urban areas already were benefiting from being in proximity to an admin urban settlement through spillover effects. Consequently, when the settlement that already was benefiting from spillover effects become admin urban itself, the positive effect is less than a settlement that did not enjoy spillover effects.

Another piece of supporting evidence of this pattern comes from examining whether settlements neighboring admin urban settlements are more or less likely to become admin urban. Table 2.16 shows the results. These include the same controls and district fixed effects I've been using for the main results. The main regressor is "adjacent to admin urban," which equal 1 if a settlement neighbors and admin urban area. Columns (1)-(3) uses HBASE data and (4)-(6) MODIS. We see that across all samples, if a settlement neighbors an admin urban settlement, it is statistically less likely for that settlement to be admin urban. This could be because settlements adjacent to admin urban areas are already enjoying the spillover effects from their neighbors. From the constituents' point of view, they are enjoying amenities of admin urban areas yet are not paying the fees and taxes of citizens living in admin urban areas. Hence, constituents would likely not want their status to change, which could be the reason behind the negative relationship between being adjacent to admin urban areas and being admin urban. Moreover, this story is congruent with the hypothesis that spillover effects explain the results from estimating equation (2.5).

2.7. Conclusion

The role of local government structure itself is often not discussed when in fact it can effect economic development, public goods access, and policy implementation. This paper's contribution is to speak to the role of local government structure in public goods provision in a developing country and explore the mechanism behind why government structure might matter. Using India's vastly different rural and urban government structures, I find that local governance does matter for public goods provision and that India's settlements with urban local governments, on average, enjoy better access to public goods such as, treated tap water, closed drainage, and light with electricity. These results hold with the inclusion of urbanization and socioeconomic controls and fixed effects. Evidence from local revenue data suggests that these results can be explained by greater degree of financial decentralization in urban admin areas. A main limitation of this paper comes from its inability to speak to the quality of public services as I only have quantity data. Moreover, given that many aspects of the rural and urban governments differ, India there may be other potential channels other than the ones explored in this paper.

2.8. Tables

Table 2.2: Breakdown of Satellite Urban

	satellite urban	
	MODIS	HBASE
admin rural	2,556	2,970
admin urban	392	513
total	2,948	3,483

This table shows the relationship between satellite urban and admin designation of rural and urban using both MODIS and HBASE data.

Table 2.3: Characteristics of Settlements by Type

	Type of Settlement						
	Village	CT	NP	Munic	M Corp	Other	Total
hh	282.19	3077.93	4652.91	13477.65	227155.12	5636.75	412.15
	(417.61)	(4207.82)	(6842.41)	(13829.00)	(343604.06)	(8331.29)	(6736.34)
pop	1395.65	13949.18	23708.60	62519.49	1043621.56	27144.75	2000.18
	(1961.49)	(19182.75)	(37915.41)	(61256.37)	(1531817.5)	(38323.64)	(30357.74)
area	4.282	6.584	11.69	21.47	93.49	14.03	4.395
	(8.593)	(6.878)	(11.32)	(24.46)	(84.19)	(24.52)	(8.942)
density	653.45	3799.05	3754.06	4531.17	10997.61	3093.03	699.32
	(1671.50)	(6016.00)	(5035.49)	(6180.98)	(7381.44)	(4173.91)	(1838.36)
frac SC	.175	.155	.149	.139	.113	.125	.174
	(.207)	(.129)	(.094)	(.088)	(.049)	(.088)	(.206)
frac ST	.197	.045	.060	.037	.025	.030	.195
	(.337)	(.107)	(.163)	(.080)	(.040)	(.054)	(.335)
frac employed	.446	.357	.361	.345	.344	.420	.445
	(.137)	(.065)	(.082)	(.051)	(.040)	(.131)	(.137)
frac male employed	.539	.534	.523	.525	.526	.618	.539
	(.098)	(.065)	(.066)	(.054)	(.051)	(.110)	(.098)
frac ag	.225	.031	.084	.038	.009	.004	.223
	(.158)	(.030)	(.085)	(.044)	(.008)	(.005)	(.158)
frac male ag	.302	.046	.116	.054	.014	.005	.299
	(.174)	(.042)	(.098)	(.061)	(.012)	(.007)	(.175)
frac dilapid. house	.064	.047	.040	.033	.026	.023	.063
	(.106)	(.048)	(.033)	(.026)	(.019)	(.043)	(.106)
frac mud roof	.212	.054	.120	.062	.036	.031	.210
	(.260)	(.086)	(.118)	(.086)	(.035)	(.046)	(.259)
frac grass wall	.120	.056	.059	.034	.019	.007	.119
	(.240)	(.113)	(.113)	(.072)	(.045)	(.018)	(.239)
frac mud wall	.357	.134	.202	.137	.097	.079	.354
	(.327)	(.137)	(.172)	(.126)	(.090)	(.104)	(.326)
N	597591	3895	2104	1702	157	95	605544

SD in parentheses

I present summary statistics for settlement characteristics and socioeconomic variables. I further divide the sample into six categories. The first column contains settlements in villages. The second column uses just census towns, which are "urban" according to the Indian census. The third column shows Nagar Panchayats, which are the smallest admin urban settlements. The next two columns are municipalities and municipal corporations, where municipalities are administratively smaller than the municipal corporations. The "other" category is mostly made up with cantonment boards.

Table 2.4: Public Goods Provision by Type

	Type of Settlement						
	Village	CT	NP	Munic	M Corp	Other	Total
tap treated	.150	.354	.401	.579	.669	.762	.154
	(.289)	(.300)	(.282)	(.279)	(.250)	(.290)	(.291)
tap untreated	.108	.107	.152	.134	.069	.101	.108
	(.246)	(.156)	(.183)	(.178)	(.088)	(.205)	(.245)
light elec	.503	.860	.787	.918	.946	.936	.508
	(.375)	(.172)	(.208)	(.085)	(.062)	(.138)	(.375)
light kerosene	.473	.128	.203	.070	.045	.054	.469
	(.373)	(.167)	(.206)	(.080)	(.059)	(.121)	(.373)
light none	.007	.004	.003	.004	.002	.003	.007
	(.061)	(.011)	(.005)	(.006)	(.002)	(.016)	(.060)
closed drainage	.044	.208	.172	.256	.470	.489	.047
	(.118)	(.203)	(.145)	(.205)	(.250)	(.314)	(.121)
open drainage	.273	.364	.525	.506	.378	.374	.276
	(.330)	(.236)	(.241)	(.225)	(.214)	(.297)	(.329)
no drainage	.681	.426	.302	.237	.150	.136	.676
	(.355)	(.268)	(.243)	(.179)	(.129)	(.230)	(.356)
cooking fuel LPG/PNG	.078	.442	.429	.582	.686	.732	.083
	(.156)	(.260)	(.215)	(.188)	(.142)	(.222)	(.164)
elem (per '000)	1.814	.326	.385	.338	.175	.473	1.795
	(9.822)	(.289)	(.549)	(.302)	(.098)	(1.325)	(9.759)
N	597591	3895	2104	1702	157	95	605544

SD in parentheses

This table shows public goods provision according to the same categorization as Table 2.4. Except for the last row that shows number of elementary schools per 1,000 people, the other variables show the average chance of having each public good.

Table 2.5: MODIS - Whole Sample with Urban Control

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.148**	0.028**	-0.025**	0.077**	0.066**	-0.143**	0.172**	0.098**
	(0.010)	(0.009)	(0.009)	(0.005)	(0.008)	(0.008)	(0.009)	(0.005)
frac urban	0.071**	0.110**	-0.112**	0.098**	0.005	-0.104**	0.199**	0.097**
	(0.012)	(0.014)	(0.013)	(0.011)	(0.012)	(0.014)	(0.011)	(0.006)
Observations	512013	512013	512013	512013	512013	512013	512013	511667
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	all	all	all	all	all	all	all	all
ctrl mean	.1478	.5157	.4660	.0440	.2805	.6754	.0824	.4130

Standard errors in parentheses and clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 2.6: MODIS - Sample: Some Urban

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.155**	0.042**	-0.041**	0.054**	0.082**	-0.137**	0.135**	0.094**
	(0.010)	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)	(0.009)	(0.005)
frac urban	0.027**	0.050**	-0.047**	0.050**	-0.025*	-0.024+	0.090**	0.038**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.010)	(0.006)
Observations	28417	28417	28417	28417	28417	28417	28417	28399
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	urban>0	urban>0	urban>0	urban>0	urban>0	urban>0	urban>0	urban>0
ctrl mean	.2415	.6711	.3135	.0899	.4007	.5093	.1933	.5181

Standard errors in parentheses

Std errors clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Tables 2.5 and 2.6 show results from direct urbanization control with a fraction urbanization covariate measured from the fraction of settlement area classified as urban from the MODIS data. Table 2.5 uses the entire sample. The outcome variables are binary variables except for the eighth column with "index." Index is the average fraction of amenities a household has access to within a settlement from amenities, (1) treated tap water (2) access to light (3) access to light via electricity (4) waste water drainage and (5) LPG/PNG gas for kitchen.

Table 2.7: MODIS - Sample: Satellite Urban

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.171**	0.024	-0.023	0.089**	0.051+	-0.141**	0.115**	0.090**
	(0.036)	(0.018)	(0.018)	(0.027)	(0.031)	(0.028)	(0.024)	(0.016)
Observations	2465	2465	2465	2465	2465	2465	2465	2462
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S urban	S urban	S urban	S urban	S urban	S urban	S urban	S urban
ctrl mean	.2359	.6708	.3175	.1493	.4233	.4273	.3108	.5570

Standard errors in parentheses and clustered at dist level

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 2.8: MODIS - Sample: Satellite Rural

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.153**	0.046**	-0.044**	0.080**	0.075**	-0.155**	0.192**	0.109**
	(0.009)	(0.009)	(0.009)	(0.005)	(0.008)	(0.008)	(0.009)	(0.006)
Observations	509548	509548	509548	509548	509548	509548	509548	509205
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S rural	S rural	S rural	S rural	S rural	S rural	S rural	S rural
ctrl mean	.1474	.5150	.4666	.0435	.2799	.6765	.0815	.4124

Standard errors in parentheses and clustered at dist level

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Tables 2.7 and 2.8 show sub-sample analyses where 2.7 and 2.8 only contain satellite urban and rural settlements respectively. The satellite urban/rural designation was made through the MODIS data. The outcome variables are binary variables except for the eighth column with "index." Index is the average fraction of amenities a household has access to within a settlement from amenities, (1) treated tap water (2) access to light (3) access to light via electricity (4) waste water drainage and (5) LPG/PNG gas for kitchen.

Table 2.9: MODIS - Private Services

	(1) priv elem	(2) priv MS	(3) priv secondary	(4) priv sr second	(5) priv bank	(6) priv elem	(7) priv MS	(8) priv secondary	(9) priv sr second
admin urban	-0.270	-0.650	-0.150	-0.087	0.016	-0.032	-0.056	-0.090	0.002
	(0.285)	(0.499)	(0.116)	(0.091)	(0.010)	(0.058)	(0.054)	(0.059)	(0.017)
S urban					-0.011				
					(0.010)				
Observations	2465	2387	2467	2469	6054	508151	507375	509523	509581
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist	dist
sample	S urban	S urban	S urban	S urban	CT +ad urban	S rural	S rural	S rural	S rural
ctrl mean	.4093	.3545	.1157	.0586	.0441	.1721	.1010	.0590	.0257

Standard errors in parentheses

Std errors clustered at dist level

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

This table tests for placebo effects using private services. I include private schooling. The first four columns are limited to satellite urban using MODIS data. Column (5) is a binary variable indicating whether settlement has private banking. This variable was only available for the sample of census towns and administratively urban settlements. The last four columns looking at private schooling in MODIS satellite rural settlements.

Table 2.10: West Bengal Per-Capita Revenue Breakdown (Rs. in 100,000)

	Total	Admin Urban	Admin Rural	Admin Urban Satellite Urban	Admin Rural Satellite Urban
Total Revenue	0.117	2.302	0.0203	2.321	0.191
	(0.896)	(3.534)	(0.257)	(5.304)	(0.895)
Transfers from State/Central Govt	0.0870	1.613	0.0194	1.936	0.183
	(0.760)	(3.129)	(0.250)	(5.326)	(0.872)
Tax Revenue	0.00476	0.102	0.000440	0.134	0.00420
	(0.0434)	(0.183)	(0.00670)	(0.187)	(0.0230)
Non-Tax Revenue	0.0252	0.586	0.000401	0.251	0.00396
	(0.359)	(1.647)	(0.00495)	(0.391)	(0.0176)
Civic Services	0.0219	0.00165	0.0229	0.00129	0.213
	(0.234)	(0.00246)	(0.239)	(0.00178)	(0.840)

This table shows the per-capita revenue breakdown of West Bengal. All numbers are in 100,0000 Rs. The first column uses whole sample, and the next two show results for admin urban and rural areas separately. The last two columns are limited to satellite urban areas and are again broken down in admin urban and rural. Standard deviations are in parentheses.

Table 2.11: West Bengal: Admin Urban and Own Source Revwnuw

	(1) frac own	(2) frac own	(3) frac tax	(4) frac tax	(5) frac nontax	(6) frac nontax
admin urban	0.019	0.115^{**}	-0.028	-0.019^{+}	0.048	0.134^{**}
	(0.049)	(0.023)	(0.023)	(0.011)	(0.046)	(0.021)
Observations	963	48484	963	48484	963	48484
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist, yr	dist, yr	dist, yr	dist, yr	dist, yr	dist, yr
sample	S urban	S rural	S urban	S rural	S urban	S rural
cluster	subdist	subdist	subdist	subdist	subdist	subdist

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

The table shows results for equation (2.3). The sample only contains West Bengal. I exclude information for financial year 2012-2013 since I only have admin urban information up until 2011. The first two columns in the table show the main outcome variable of interest – fraction own-source revenue. Columns (3)-(4) show the relationship between admin urban and fraction of tax and (5)-(6) fraction of non-tax revenue.

Table 2.12: West Bengal Own Source Revenue: Satellite Urban (MODIS)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
frac own	0.008	0.080^{+}	-0.077^{+}	-0.040	0.121^{+}	-0.081	0.167^{**}	0.067^{*}
	(0.099)	(0.044)	(0.043)	(0.045)	(0.064)	(0.073)	(0.057)	(0.029)
Observations	963	963	963	963	963	963	963	963
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S urban	S urban	S urban	S urban	S urban	S urban	S urban	S urban
cluster	subdist	subdist	subdist	subdist	subdist	subdist	subdist	subdist

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 2.13: West Bengal Own Source Revenue: Satellite Rural (MODIS)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
frac own	0.164^{**}	0.171^{**}	-0.160^{**}	0.030^{**}	0.062^{*}	-0.092^{**}	0.139^{**}	0.114^{**}
	(0.048)	(0.037)	(0.035)	(0.009)	(0.027)	(0.033)	(0.033)	(0.022)
Observations	48436	48436	48436	48436	48436	48436	48436	48436
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S urban	S urban	S urban	S urban	S urban	S urban	S urban	S urban
cluster	subdist	subdist	subdist	subdist	subdist	subdist	subdist	subdist

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Tables 2.12 and 2.13 show sub-sample analyses limited to West Bengal. Unlike Tables 2.7 and 2.8, we look at the relationship between fraction own-source revenue and public goods access. The satellite urban/rural designation was made through the MODIS data. The outcome variables are binary variables except for the eighth column with "index." Index is the average fraction of amenities a household has access to within a settlement from amenities, (1) treated tap water (2) access to light (3) access to light via electricity (4) waste water drainage and (5) LPG/PNG gas for kitchen.

Table 2.14: Spillover Effects: Satellite Urban (MODIS)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.173**	0.125**	-0.126**	0.046	0.019	-0.065	0.215**	0.115**
	(0.056)	(0.040)	(0.040)	(0.060)	(0.070)	(0.046)	(0.052)	(0.024)
admin urban X urban nbr	0.003	-0.130**	0.133**	0.077	0.022	-0.099	-0.127+	-0.030
	(0.091)	(0.047)	(0.048)	(0.072)	(0.085)	(0.062)	(0.065)	(0.037)
Observations	2462	2462	2462	2462	2462	2462	2462	2459
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr
sample	S urban	S urban	S urban	S urban	S urban	S urban	S urban	S urban

Standard errors in parentheses

Std errors clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 2.15: Spillover Effects:: Satellite rural (MODIS)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.162**	0.059**	-0.060**	0.081**	0.078**	-0.159**	0.217**	0.119**
	(0.009)	(0.010)	(0.010)	(0.005)	(0.009)	(0.009)	(0.008)	(0.005)
admin urban X urban nbr	-0.040+	-0.063**	0.068**	-0.002	-0.014	0.016	-0.133**	-0.051**
	(0.023)	(0.014)	(0.013)	(0.012)	(0.017)	(0.022)	(0.018)	(0.013)
Observations	505807	505807	505807	505807	505807	505807	505807	505479
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr
sample	S rural	S rural	S rural	S rural	S rural	S rural	S rural	S rural

Standard errors in parentheses

Std errors clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Tables 2.14 and 2.15 show results for MODIS satellite urban and rural samples. The interaction term is binary variable of being admin urban interacted with another binary variable, which equals 1 when the settlement neighbors an admin urban settlement.

Table 2.16: Chances of Being Admin Urban

	(1) admin urban	(2) admin urban	(3) admin urban	(4) admin urban	(5) admin urban	(6) admin urban
adjacent to admin urban	-0.020**	-0.099**	-0.017**	-0.020**	-0.090**	-0.018**
	(0.001)	(0.012)	(0.001)	(0.001)	(0.016)	(0.001)
Observations	516771	3274	513497	516771	2552	514219
controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	subdist	subdist	subdist	subdist	subdist	subdist
sample	all	S urban	S rural	all	S urban	S rural
cluster	dist	dist	dist	dist	dist	dist
data	hbase	hbase	hbase	modis	modis	modis

Standard errors in parentheses

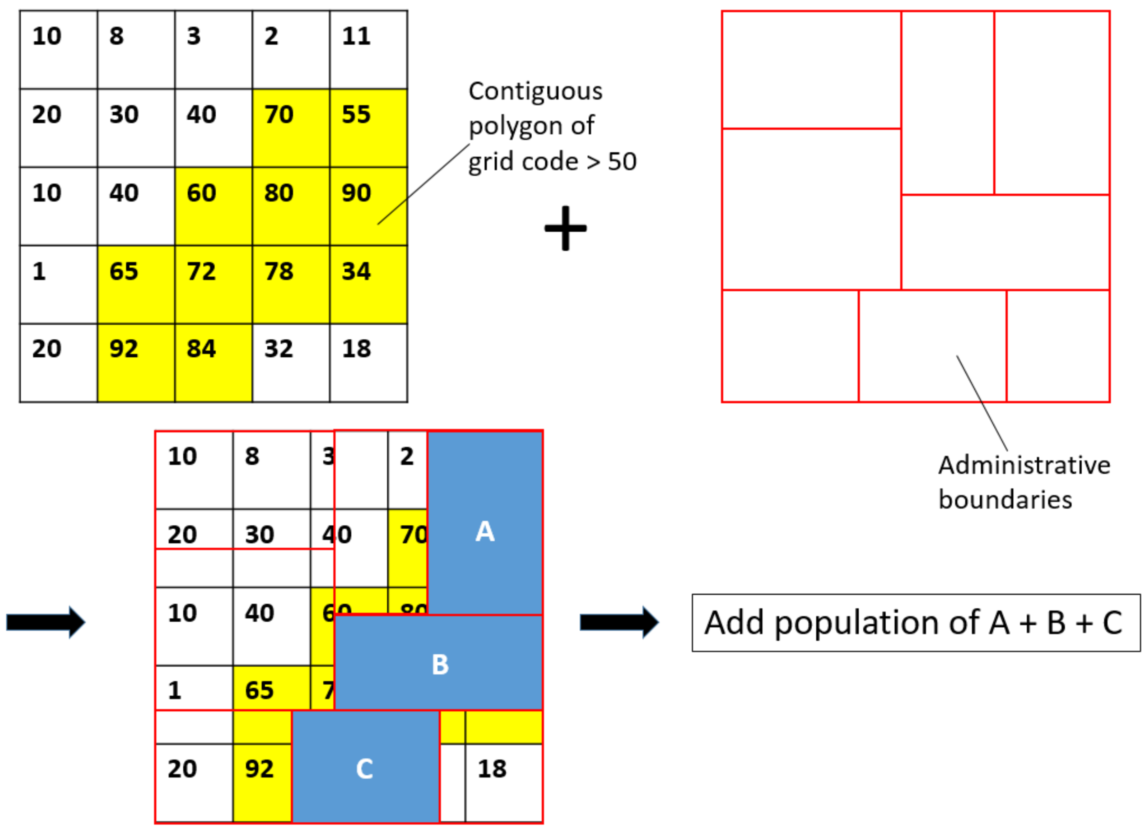
Std errors clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

The above shows the effect of having an admin urban settlement as a neighbor on chances of being admin urban itself. These include the same controls and district fixed effects I've been using for the main results. The main regressor is "adjacent to admin urban," which equal 1 if a settlement neighbors and admin urban area. Columns (1)-(3) uses HBASE data and (4)-(6) MODIS.

2.9. Figures

Figure 2.1: Satellite Urban Designation



This figure illustrates the process I use to designate a settlement "satellite urban". The first gridded image in Figure 2.1 represents the satellite image, where the number in each square, called grid code, signifies the imperviousness level, i.e. the level of human builtup. From this, I group together contiguous grids that are over a certain threshold (in this case, the threshold is 50). I then overlay the satellite image with the administrative boundaries (image on the top-right in this figure). Let's call the administrative boundaries overlapping with the contiguous polygon "candidate" boundaries. As it can be seen from the bottom image, area B is completely within the contiguous polygon and hence is a "candidate". Boundaries A and C overlap with both the grid code $>$ 50 contiguous polygon and the rest. Since the contiguous polygon does take up the most area for these two boundaries, we include settlements A and C as candidates. Now we have contiguous *settlements* consisting of areas A, B, and C. Finally, we add up all the contiguous candidates' population and see if this exceeds 50,000. If so, I designate A, B, and C as satellite urban.

Figure 2.2: Jhalda, West Bengal – admin urban

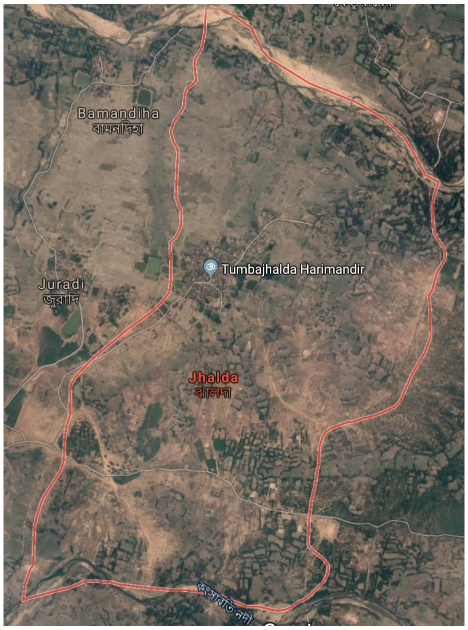
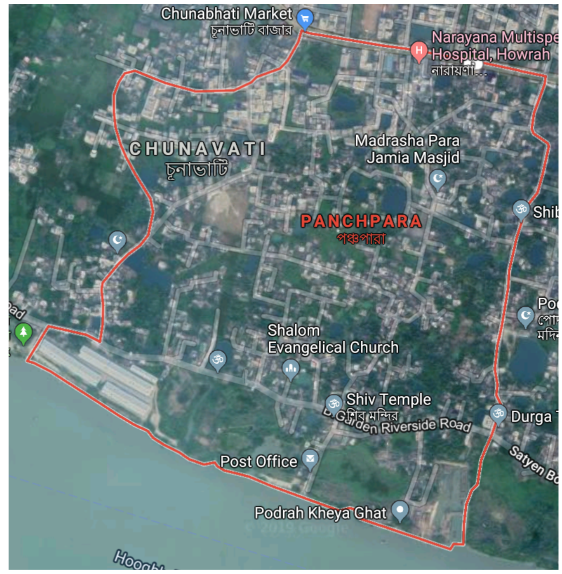


Figure 2.3: Panchpara, West Bengal – admin rural

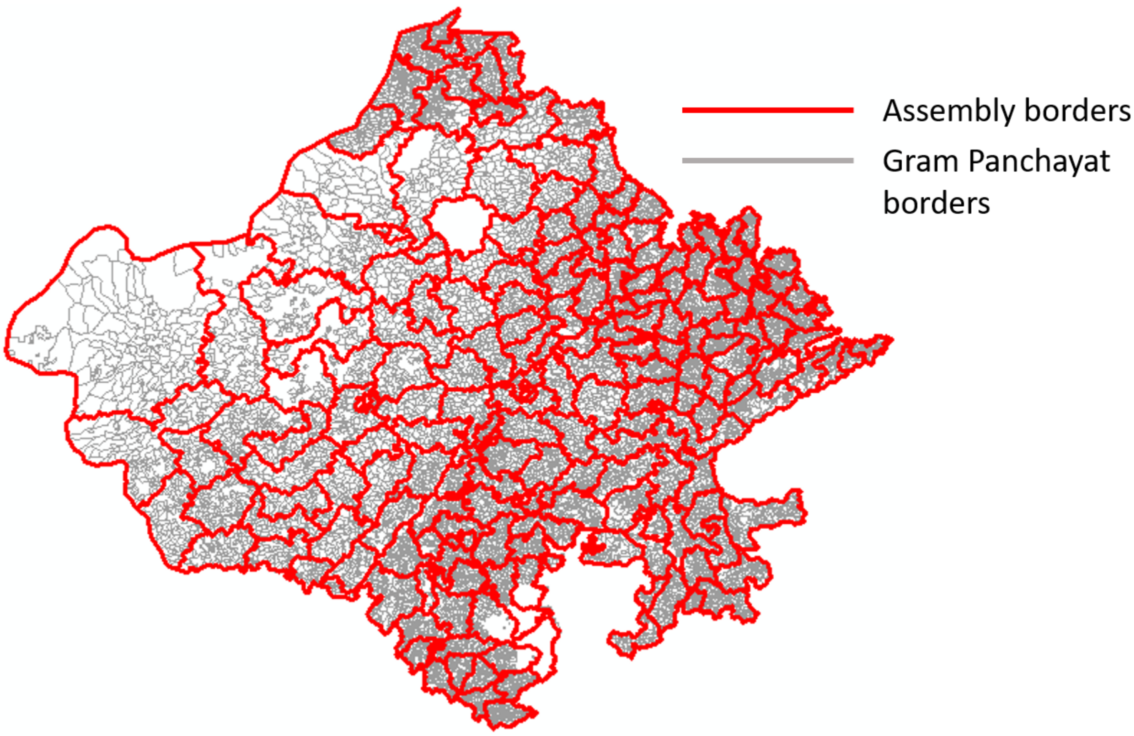


These images are taken from Google satellite maps. Figure 2.2 is a satellite image of Jhalda in West Bengal. Jhalda is a municipality, or admin urban, with an urban local government. In Figure 2.3 we have Panchpar, also in West Bengal. Panchpara is actually a village with a rural government.

APPENDIX

A.1. Chapter 1

Figure A.1.1: Rajasthan Borders



This figure shows the state of Rajasthan in India. The red thicker borders show the assembly boundaries and the gray thinner borders are gram panchayat boundaries.

Table A.1.1: Size of Gram Panchayats

	Households	Population
mean	416.7551	2649.835
p1	121	799
p25	232	1533
p50	323	2126
p75	529	3318
p99	1463	8964
Unique GP	6126	

This table describes the number of households and population within sample gram panchayats. I report the average, 1st percentile, 25th percentile, median, 75th percentile and 99th percentile.

Table A.1.2: Triple-Difference Effects on Households Worked

	Households Worked		
	(1) tot HH	(2) SC	(3) non-SC
Inter SC × Local SC × post	2.63**	1.06*	1.56
	(1.29)	(0.59)	(0.99)
Local SC × post	-3.32***	0.25	-3.57***
	(0.80)	(0.23)	(0.68)
Inter SC × post	-2.21	0.24	-2.45*
	(1.80)	(0.74)	(1.32)
Observations	588096	588096	588096
R^2	0.477	0.400	0.486
outcome mean	25.21	7.10	18.12
state-time FE	X	X	X
GP FE	X	X	X
unique GP	6126	6126	6126

Standard errors clustered at assembly level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The outcome variables reflect the number of households worked in a given gram panchayat monthly. The first column shows results for total monthly households that worked NREGS jobs, and columns (2) and (3) are broken down into SC households and non-SC households respectively. The first row of coefficients show the triple-difference effects. All estimates include state-time fixed effects and gram panchayat fixed effects. I report outcome variable means and number of unique gram panchayats as well. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.1.3: Winsorized Results

	Days		
	(1)	(2)	(3)
	tot days	SC	non-SC
Inter SC × Local SC × post	28.79*	12.25**	13.95
	(16.08)	(6.037)	(13.33)
Local SC × post	-46.04***	3.994	-51.31***
	(10.97)	(2.918)	(9.060)
Inter SC × post	-16.02	5.630	-22.21
	(27.80)	(9.087)	(22.07)
Observations	588,096	588,096	588,096
R^2	0.471	0.384	0.481
outcome mean	322.241	89.285	230.588
state-time FE	X	X	X
GP FE	X	X	X
unique GP	6,126	6,126	6,126

Standard errors clustered at assembly level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The outcome variables winsorized at the 99 percent level and reflect the summation of number of days worked in a given gram panchayat monthly, but winsorized. Note that this is not equivalent to per-household work-days. The first column shows results for all monthly NREGS work-days, and column (2) and (3) are broken down into days worked by only SC households and non-SC households respectively. The first row of coefficients show the triple-difference effects. All estimates include state-time fixed effects and gram panchayat fixed effects. I report outcome variable means and number of unique gram panchayats as well.

Table A.1.4: Results with Interacted Controls

	Days		
	(1)	(2)	(3)
	tot days	SC	non-SC
Inter SC × Local SC × post	37.03*	16.59*	20.45
	(21.32)	(8.697)	(17.48)
Local SC × post	-53.24***	-5.145	-48.10***
	(13.95)	(4.042)	(11.69)
Inter SC × post	-22.45	2.883	-25.33
	(30.86)	(10.81)	(24.30)
Observations	540,000	540,000	540,000
R^2	0.442	0.376	0.445
outcome mean	384.084	102.647	281.438
state-time FE	X	X	X
GP FE	X	X	X
controls × post	X	X	X
unique GP	5,625	5,625	5,625

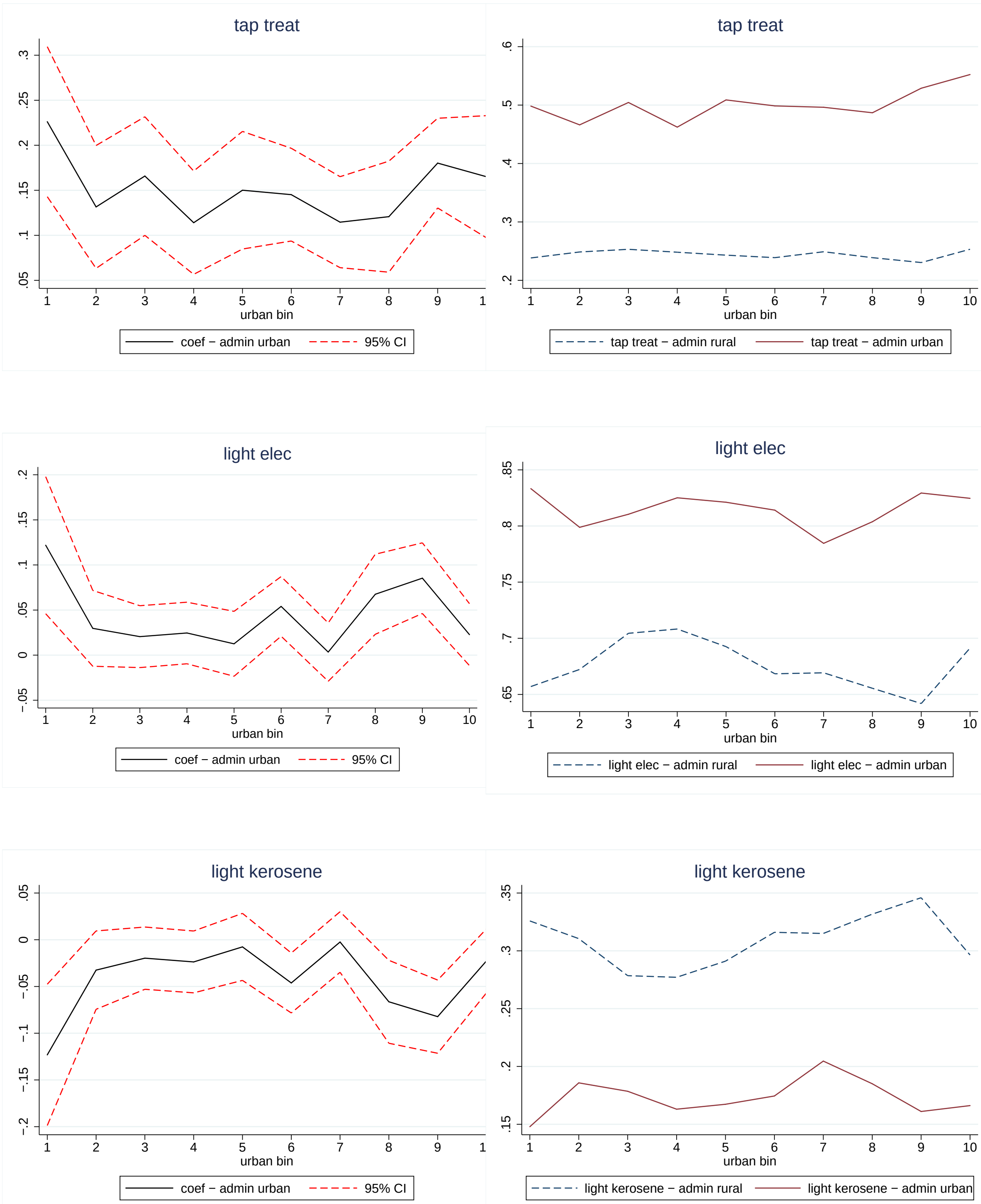
Standard errors clustered at assembly level

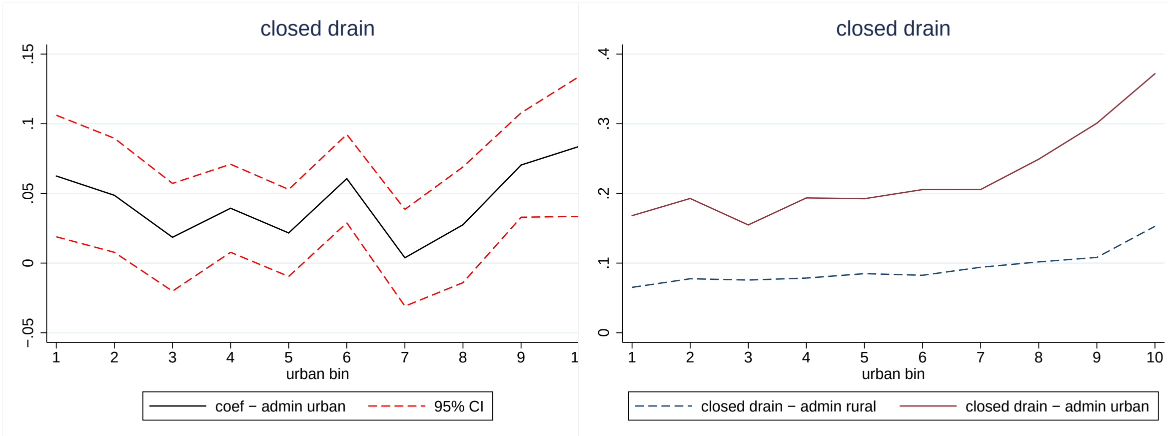
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

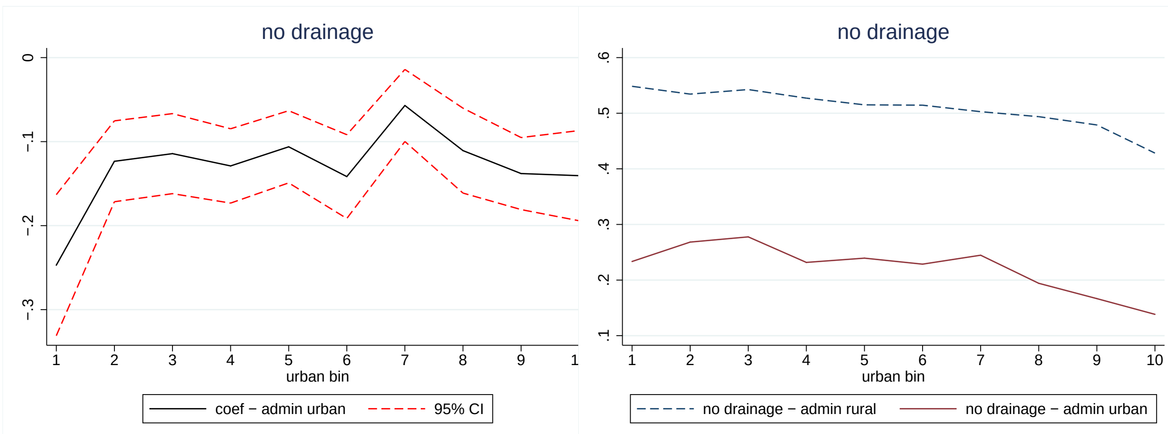
The outcome variables are the summation of number of days worked in a given gram panchayat monthly. Note that this is not equivalent to per-household work-days. The first column shows results for all monthly NREGS workdays. Columns 2 and 3 are broken down into days worked by only SC households and non-SC households, respectively. The first row of coefficients show the triple-difference effects. All estimates include state-time fixed effects and gram panchayat fixed effects. These results also include controls for total number of households, number of SC households, and area interacted with the "post" indicator variable. The number of observations are not equal to other results as not every gram panchayat has these baseline variables available.

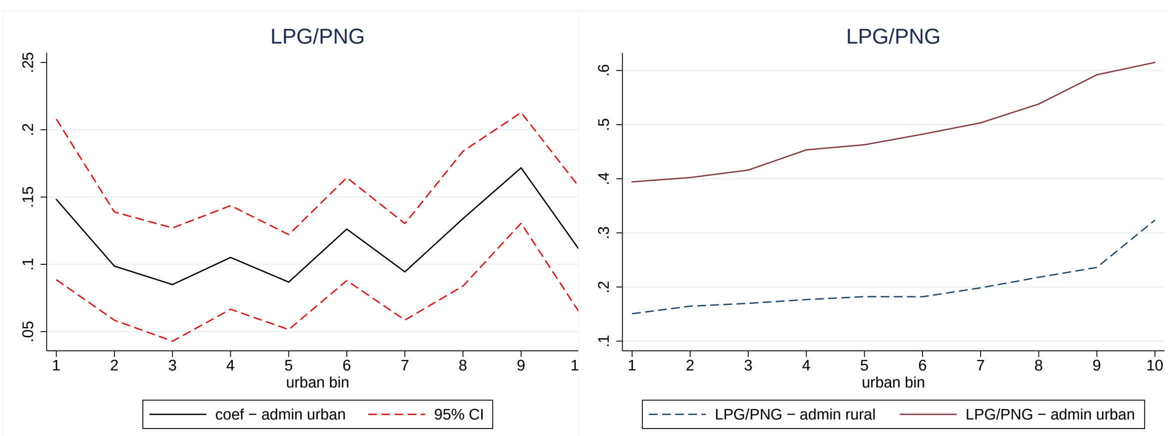
A.2. Chapter 2

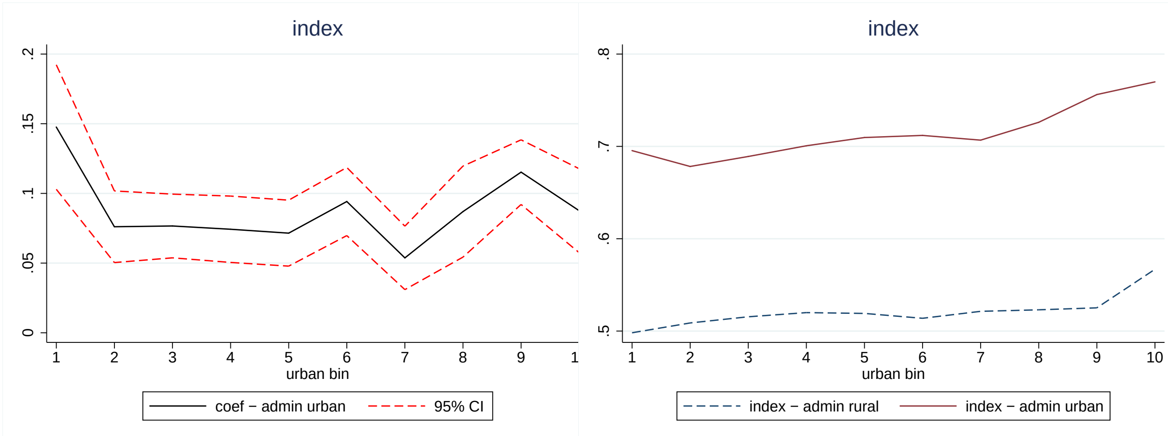
Figure A.2.1: Public Goods Access and Admin Urban




closed drain
urban bin
coef − admin urban
95% CI
closed drain
urban bin
closed drain − admin rural
closed drain − admin urban


no drainage
urban bin
coef − admin urban
95% CI
no drainage
urban bin
no drainage − admin rural
no drainage − admin urban


LPG/PNG
urban bin
coef − admin urban
95% CI
LPG/PNG
urban bin
LPG/PNG − admin rural
LPG/PNG − admin urban



The graphs use just the settlements with urban area > 0. The figures have level of urbanization on the x-axis. I created "urban bins" using a linear combination of fraction of area urban using MODIS data, population, and density. For each bin, I estimate equation (2.1) separately. The coefficient on *admin_urban* and 95% confidence intervals are reported in the graphs on the left side. The graphs on the right hand side are the predicted outcomes for admin rural and admin urban separately.

Table A.2.1: HBASE - Sample: Satellite Urban

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.147**	0.026*	-0.028*	0.081**	0.039+	-0.120**	0.116**	0.081**
	(0.030)	(0.012)	(0.011)	(0.022)	(0.022)	(0.018)	(0.018)	(0.012)
Observations	3199	3199	3199	3199	3199	3199	3199	3195
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S urban	S urban	S urban	S urban	S urban	S urban	S urban	S urban
ctrl mean	.3183	.8315	.1563	.1875	.4915	.3208	.4239	.6497

Standard errors in parentheses and clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A.2.2: HBASE - Sample: Satellite Urban

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.158**	0.048**	-0.046**	0.079**	0.081**	-0.160**	0.194**	0.112**
	(0.009)	(0.009)	(0.009)	(0.004)	(0.008)	(0.009)	(0.009)	(0.006)
Observations	493358	493358	493358	493358	493358	493358	493358	493039
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S rural	S rural	S rural	S rural	S rural	S rural	S rural	S rural
ctrl mean	.1483	.5181	.4642	.0438	.2815	.6745	.0816	.4136

Standard errors in parentheses and clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

A.2.1 and A.2.2 show sub-sample analyses where A.2.1 and A.2.2 only contain satellite urban and rural settlements respectively. The satellite urban/rural designation was made through the HBASE data. The outcome variables are binary variables except for the eighth column with "index." Index is the average fraction of amenities a household has access to within a settlement from amenities, (1) treated tap water (2) access to light (3) access to light via electricity (4) waste water drainage and (5) LPG/PNG gas for kitchen.

Table A.2.3: HBASE - Private Services

	(1) priv elem	(2) priv MS	(3) priv secondary	(4) priv sr second	(5) priv bank	(6) priv elem	(7) priv MS	(8) priv secondary	(9) priv sr second
admin urban	-0.152	-0.219	-0.049	-0.051	0.016	-0.027	-0.060	-0.087	0.003
	(0.228)	(0.232)	(0.059)	(0.054)	(0.011)	(0.056)	(0.053)	(0.058)	(0.017)
S urban					-0.001				
					(0.004)				
Observations	3203	3149	3204	3205	6054	507413	506613	508786	508845
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist	dist
sample	S urban	S urban	S urban	S urban	CT +ad urban	S rural	S rural	S rural	S rural
ctrl mean	.2962	.2052	.1183	.0597	.0441	.1724	.1014	.0589	.0256

Standard errors in parentheses

Std errors clustered at dist level

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

This table tests for placebo effects using private services. I include private schooling. The first four columns are limited to satellite urban using HBASE data. Column (5) is a binary variable indicating whether settlement has private banking. This variable was only available for the sample of census towns and administratively urban settlements. The last four columns looking at private schooling in HBASE satellite rural settlements.

Table A.2.4: Admin Urban Transfer Breakdown

	Admin Urban Transfer Breakdown				
	frac salary/pension	frac untied	frac fixed	frac dev	frac other
admin urban	.198	.147	.069	.504	.079
	(.115)	(.058)	(.032)	(.135)	(.065)
N	126	126	126	126	126

SD in parentheses

This the breakdown of the transfers to admin urbna areas. Frac dev are fraction transfered for development project.

Table A.2.5: West Bengal Own Source Revenue: Satellite Urban (HBASE)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
frac own	-0.153	0.194**	-0.185**	0.154	0.124	-0.277*	0.489**	0.163**
	(0.190)	(0.053)	(0.049)	(0.152)	(0.134)	(0.100)	(0.091)	(0.052)
Observations	73	73	73	73	73	73	73	73
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S urban	S urban	S urban	S urban	S urban	S urban	S urban	S urban
cluster	subdist	subdist	subdist	subdist	subdist	subdist	subdist	subdist

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A.2.6: West Bengal Own Source Revenue: Satellite Rural (HBASE)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
frac own	0.263**	0.229**	-0.220**	0.035*	0.084+	-0.119*	0.202**	0.163**
	(0.073)	(0.060)	(0.059)	(0.014)	(0.044)	(0.053)	(0.054)	(0.036)
Observations	9682	9682	9682	9682	9682	9682	9682	9682
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist	dist	dist	dist	dist	dist	dist	dist
sample	S rural	S rural	S rural	S rural	S rural	S rural	S rural	S rural
cluster	subdist	subdist	subdist	subdist	subdist	subdist	subdist	subdist

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Tables A.2.5 and A.2.6 show sub-sample analyses limited to West Bengal. Unlike Tables A.2.1 and A.2.2, we look at the relationship between fraction own-source revenue and public goods access. The satellite urban/rural designation was made through the MODIS data. The outcome variables are binary variables except for the eighth column with "index." Index is the average fraction of amenities a household has access to within a settlement from amenities, (1) treated tap water (2) access to light (3) access to light via electricity (4) waste water drainage and (5) LPG/PNG gas for kitchen.

Table A.2.7: Spillover Effects: Satellite Urban (HBASE)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.137**	0.073**	-0.076**	0.093*	-0.011	-0.081**	0.172**	0.089**
	(0.050)	(0.024)	(0.023)	(0.038)	(0.037)	(0.028)	(0.030)	(0.019)
admin urban X urban nbr	0.005	-0.087**	0.089**	-0.029	0.049	-0.020	-0.113**	-0.031
	(0.068)	(0.027)	(0.027)	(0.045)	(0.047)	(0.038)	(0.040)	(0.026)
Observations	3199	3199	3199	3199	3199	3199	3199	3195
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr
sample	S urban	S urban	S urban	S urban	S urban	S urban	S urban	S urban

Standard errors in parentheses
Std errors clustered at dist level
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A.2.8: Spillover Effects: Satellite Rural (HBASE)

	(1) tap treat	(2) light elec	(3) light kerosene	(4) closed drain	(5) open drain	(6) no drainage	(7) LPG/PNG	(8) index
admin urban	0.165**	0.065**	-0.065**	0.079**	0.085**	-0.165**	0.222**	0.123**
	(0.009)	(0.010)	(0.010)	(0.005)	(0.008)	(0.008)	(0.007)	(0.005)
admin urban X urban nbr	-0.028	-0.059**	0.063**	0.011	-0.011	0.000	-0.126**	-0.043**
	(0.024)	(0.014)	(0.014)	(0.013)	(0.018)	(0.024)	(0.019)	(0.014)
Observations	505977	505977	505977	505977	505977	505977	505977	505640
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr	dist X nbr
sample	S rural	S rural	S rural	S rural	S rural	S rural	S rural	S rural

Standard errors in parentheses
Std errors clustered at dist level
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Tables 2.14 and 2.15 show results for MODIS satellite urban and rural samples. The interaction term is binary variable of being admin urban interacted with another binary variable, which equals 1 when the settlement neighbors an admin urban settlement.

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