Essays in Development Economics

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M.A. Economics, University of Virginia, 2018

A Dissertation presented to the Graduate Faculty
of the University of Virginia in Candidacy for the Degree of Doctor of Philosophy

Department of Economics

University of Virginia
December, 2024

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Abstract: Essays in Development Economics

I study a variety of development policies in the context of India. In the first chapter, I focus on the administrative decentralization generated by the creation of new districts in the state of Telangana in India. On the one hand, the resulting smaller districts could experience improved governance by reducing bureaucratic burden and making them more accessible to the people. On the other hand, reshuffling of civil servants following district reorganization could result in disruption of routine functioning, lower administrative capacity, and higher operational costs in newly created districts. I examine the short-run effects of this policy change using a spatial regression discontinuity approach and comparing villages across the border areas between the parent and the newly created district that had similar characteristics prior to the policy change. Examining village-level data on various government schemes and economic outcomes, I find mixed results with positive impact under scheme with bottom-up implementation and negative or no effect under top-down programs. The positive effect is stronger in villages that are closer to the district headquarter and in villages with high level of civic participation suggesting the role of greater lobbying as district administration moves closer to people.

For the second chapter I ask: can cash transfers to farmers boost agricultural productivity? On the one hand, cash transfers could increase productive investment if farmers face liquidity constraints. On the other hand, cash transfers could increase

consumption and decrease labor supply through an income effect. Additionally, such transfers could have general equilibrium effects, such as raising the price of farm inputs, which may to dampen the intended effect. Using household-level data and a difference-in-differences approach, I investigate how transfers made to farmers under the Rythu Bandhu Scheme in the Indian state of Telangana affected their labor supply and the farm related outcomes. These transfers were large and unconditional, though labeled as investment support, and targeted only to landowning agricultural households. I document significant gains in crop yield due to an increase in expenditure on farm inputs and assets, and a greater allocation of household labor to own farm cultivation for larger agricultural households. Smaller farmers experience modest gains in input expenditure and a shift to agriculture labor, away from own self employment in agriculture. Further, I find no evidence of negative spillover effects on tenant farmers or non-agricultural households who did not receive transfers.

The third chapter considers whether women leaders find it difficult to lobby for discretionary development funds and funds contingent on subjective official evaluation, within a male-dominated political system and a male-biased society. To test this hypothesis, I exploit randomly assigned electoral gender quotas and a panel data set on loans released under a large public sector capital investment scheme in India. My results show that village councils reserved for women have a lower likelihood of receiving a loan under this program compared to unreserved, largely male-headed village

councils. These results are robust to the inclusion of controls for Sarpanch characteristics but heterogeneous with the village council distance to the district headquarter. However, conditional on getting a loan sanctioned, women-reserved councils are able to secure greater loan disbursal than those unreserved. My findings are consistent with existing evidence on the gains from women leadership in spite of the of the barriers that persist post reservation.

JEL Classifications: D72, H41, H77, I38, J16, J43, O12

Keywords: Decentralization, cash transfers, agricultural investment, agricultural labor market, gender, political economy

Acknowledgments

I would like to express my heartfelt gratitude to all those who supported me throughout the journey of completing this thesis. First and foremost, I am deeply thankful to my advisor, Sandip Sukhtankar, for his invaluable guidance, encouragement, and expertise. Your insights and feedback have been instrumental in shaping my research.

I also extend my appreciation to my committee members, Sheetal Sekhri, Shan Aman-Rana, and Gaurav Chiplunkar, for their constructive critiques and suggestions, which enriched my work.

A special thanks to my colleagues and friends for their unwavering support and solidarity during this process. Your encouragement helped me stay motivated during challenging times.

Lastly, I am immensely grateful to my family for their love, patience, and understanding. Your belief in me has been my greatest motivation.

Thank you all for being a part of this journey.

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Impact of Administrative Decentralization on Local Development: Evidence from India

1.1 Introduction

Beginning in the 1970s, many developing countries carried out decentralization reforms both to create public institutions that are more accessible and inclusive and to improve the efficiency of public goods and service delivery. This was carried out to varying degrees and along multiple dimensions including political, fiscal, administrative, and economic with mixed results (Rondinelli, 1983). At the same time, governments were implementing a popular policy of creating new, smaller sub-national units[1] by way of reorganizing the existing ones. This phenomenon was witnessed in countries undergoing expansive decentralization reforms across Asia and Africa including Vietnam, Indonesia, Malawi, Uganda, Kenya, and Ghana. And while these policy measures are related to an extent, the two are not identical.

Theoretically, similar arguments can be made both in favor and opposition

[1]The process of creating new sub-national government units is also referred to as government fragmentation (Pierskalla, 2016), administrative unit proliferation (Grossman and Lewis, 2014), district reorganization/splitting etc. I will be using these terms interchangeably.

of government fragmentation as in the case of decentralization. On the one hand, newer units are likely to smaller, closer to their respective administrative centers, and more homogeneous. This could improve governance by allowing customization of policy to local needs due to better information, and encouraging yardstick competition (Tiebout, 1956; Oates, 1993; Besley and Case, 1995). On the other hand, smaller jurisdictions lose out on potential benefits from economies of scale in catering to a large population base (Prud'homme, 1995a). Further, the process of reorganization could lead to disruption of routine functioning and efficiency losses in the short-run.

The degree to which the process of administrative unit proliferation embodies the essence of decentralization depends on the specific institutional context in which it is carried out. For instance, in a country such as Indonesia, the local legislatures hold authority over the district administration and exercise the power to elect the district head, approve the local budget, and pass local laws (Pierskalla, 2016). On the other, we can have an administrative setup where the bureaucracy operates independently, at least in principle, of the elected executive, as in the case of India. Therefore, creating new local units can take different forms ranging from deconcentration to devolution. Recently, administrative unit proliferation has re-emerged as a frequent state response to population growth and state capacity needs. The phenomenon motivates the inquiry in this paper, where I investigate the effect of district reorganization on development outcomes within the context of the Indian state of Telangana.

Indian states rely on a nested, hierarchical administrative set-up to enforce government rules and regulations and execute government policies. The district is the principal administrative unit and acts a bridge between the government and the people. In October 2016, the Government of Telangana carved out 21 new districts from its existing 10 districts with the expressed aim of improving overall administration and the implementation of government schemes in the state. The more than doubling of districts was an unprecedented move in India, though it was soon followed to varying degrees by other states within the country. Given the purely bureaucratic nature of district administration, this policy change provides an ideal setting to isolate the effect of administrative decentralization without corresponding political and/or fiscal devolution in the context of a developing country.

Using village[2]-level administrative data, I implement a spatial regression discontinuity design and compares villages close (10km) to the border between the old and the adjoining new district[3]. Before district reorganization, there is minimal difference in terms of demographic and geographic covariates between these areas. Hence, any difference in outcomes between the areas on the old and the new side of the district boundary can plausibly be attributed to administrative decentralization. Using data on India's national workfare program, National Rural Employment Guarantee Scheme (NREGS), my baseline RD estimates show that the number of person-days of work generated under the scheme from 2017-18 to 2022-23 is 13.7% higher for new district villages relative to old district villages. These results are robust to employing alternative bandwidths and global polynomial approach.

I also consider the impact on other government programs. Using Mission Antyodaya (MA) data, I combine the number of beneficiaries under different welfare

[2]or at the village cluster known as Gram Panchayat

[3]In the rest of the paper, I will be using following terminology for different jurisdictions: "parent" and "splinter" district refers to districts defined by the pre- and post-policy district boundaries respectively, "old" and "new" district refers to the splinter district with the original and newly established headquarter respectively.

schemes, as a proportion of the total eligible beneficiaries, to create an index. I find that villages under new districts have a 0.107 standard deviation lower value of this index relative to old district villages. However, looking at the each scheme individually, I find that the result is being driven by two schemes: a cash incentive scheme for pregnant mothers and a capacity building and training scheme for the elected GP representatives. Without additional information, it is difficult to pin-point the underlying source of this variation although it is worth noting that the two schemes differ from the others included under the index in the extent and nature of district administration's involvement in their implementation. At the same time, looking at village-level infrastructure, I find no significant difference in the new district villages. The top-down nature of the provision of infrastructure and the implementation of the two schemes discussed above in contrast to the bottom-up process of NREGS helps in reconciling these two sets of results.

In order to understand the underlying mechanism driving my results, I perform the following tests which are motivated by the decentralization literature. First, in order to test for leakages and corruption, I look at the amount of wages disbursed to workers and different sub-categories of total expenditure incurred under NREGS. I find that both the total amount disbursed into workers' accounts as well as the expenditure on unskilled labor is higher for new district villages compared to old district villages. There is no significant difference in the extent of material or administrative expenditure. This suggests that (1) the person-days results are less likely to be due to "ghost workers" that only exist on paper, and (2) that if the labor expenditure were fudged, we should see a similar effect on material expenditure which provides greater scope for misreporting but that is not the case.

Second, I find that my main RD estimate for person-days generated under NREGS is heterogeneous along distance to the district headquarter. Specifically, I find that the main treatment effect is driven by villages within 30km of the newly established district HQ. This lends support to the distance channel. I also find evidence of heterogeneous effects across different magnitudes of change in the degree of caste concentration resulting from the district reorganization. Further, treatment effect is higher in new district villages with greater voter turnout in local GP elections held after district reorganization. Thus, I interpret the main results as unlikely to be caused by greater homogeneity within districts after the reorganization. Taken together, these results suggest that improved NREGS implementation could be due to greater collective action and lobbying of bureaucrats by local leaders and citizens as the district administration is closer following district reorganization.

This paper contributes to two main strands of literature. First, it builds on the existing work on administrative unit proliferation. Prior studies have largely focused on the political incentives for the creation of new administrative units. These include opportunity for expanding ethnic patronage, potential electoral benefits, and suppressing political opposition (Malesky, 2009; Green, 2010; Hassan, 2016; Gottlieb et al., 2019). More recent work in this area has attempted to look at the effect of this policy measure on outcomes such as violence (Pierskalla and Sacks, 2017; Bazzi and Gudgeon, 2016), public goods provision (Grossman and Lewis, 2014; Grossman et al., 2017; Dahis and Szerman, 2021), reported life satisfaction (Flèche, 2021) and economic growth (Jia et al., 2021; Cassidy and Velayudhan, 2022). However, majority of these studies: (1) are situated in the context where creation of new units followed more comprehensive decentralization reforms, or (2) rely on difference-in-differences approach[4]. My paper is able to build on the existing literature by looking at the effect of district splitting without contemporaneous, complementary policy changes and by adopting a spatial regression discontinuity approach to minimize threats from omitted variable bias.

Second, there is a vast body of research that looks at the impact of decentralization on delivery of public goods and services, especially in the context of developing countries. Recent paper by Faguet (2021) reviews and synthesizes the theoretical arguments as well as the empirical evidence offered in the extensive literature. However, these studies have predominantly examined the devolution of political powers (in the case of developing countries) and fiscal powers (in the case of developed countries) to local self-governments. Few papers have attempted to isolate the effect of administrative decentralization on public goods provision (Chaudhary and Iyer, 2024). I complement this literature by looking at a kind of administrative decentralization that take places through administrative unit proliferation. I find some suggestive evidence in favor of lower distance to district headquarter being the underlying mechanism. This is consistent with the findings of Asher et al. (2018) who study the impact of distance to headquarter on public goods provision and economic outcomes in Indian villages.

The remainder of the paper is organized as follows. Section 2 discusses related literature, Section 3 describes the institutional context, while section 4 outlines the conceptual framework. Section 5 details the data and Section 6 explains the empirical approach, section 7 provides results, and section 8 investigates mechanisms. Section

[4]A related strand of literature looks at the effect of polity size on public service delivery. For instance, (Narsimhan and Weaver, 2023) looks at the effect of GP size on local outcomes in Indian villages.

9 discusses the results and section 10 concludes.

1.2 Related Literature

Evaluating the effect of district reorganization draws on the related literature on administrative unit proliferation, optimal polity size, and decentralization. In this section, I highlight the key findings from recent studies on these topics, position my paper in relation to these studies, and discuss my contribution to the field. Administrative unit proliferation (Grossman and Lewis (2014)) or government fragmentation (Grossman et al. (2017)) refers to the phenomenon of creating new, generally smaller, administrative units by reorganizing the existing ones. Majority of the literature on this subject has focused on the political motives behind the policy decision. However, there's growing interest in exploring its impact on development outcomes such as economic growth and public goods provision.

For instance, using cross-country data on the number of top-tier regional governments in sub-Saharan Africa, Grossman et al. (2017) find temporary improvement in health and education outcomes in newly created units which tapers off over time. At the same time, they observe a worsening of outcomes in the mother units. They posit that this is a result of redistribution of fiscal and administrative resources to these regions. Asher and Novosad (2015) find a similar improvement in education levels when looking at the newly created states in India which was not evident in the parent states. Gottlieb et al. (2019) is able to provide suggestive evidence of redistributive policy choice by showing that a vote-maximizing incumbent targets benefits to rural communities in Senegal either in the form of a new administrative unit or greater provision of local public goods depending on whether or not there is a history of reciprocal targeting to the group. However, these studies focus on units that have a publicly elected body which conflates the effect of political influences with administrative.

More rigorous evaluation and robustly identified estimates of the impact of creating new administrative units on local outcomes is provided by Jia et al. (2021). They find that following the elevation of Chongqing from prefecture to province level, the region witnessed a significant and sustained increase in the economic growth as proxied by nighttime light intensity. Further, the new province experienced higher industrial output per capita, urbanization rate, and non-farm employment. The authors show that these effects are driven by higher capital expenditure, greater provision of public goods and services, and more business-friendly regulatory environment. This study is situated in the context of China, an authoritarian regime with a stringent system of rewards and punishments that limits the extent of bureaucratic corruption and elite capture by powerful local actors. This is in sharp contrast to the existing conditions in developing countries in several ways. First, in India, bureaucratic appointments are lifetime positions and promotions are not strongly tied to performance rather on the number of vacancies and the number of years in service. Second, corruption is widespread, as excessive regulations and discretionary powers enable collusion between bureaucrats and political and local agents.

A key rationale behind creating new administrative units is that the reduction in unit size would reduce bureaucratic burden and improve governance. To test this hypothesis, Narsimhan and Weaver (2023) exploit the population-based rule for creation of local government in the Indian state of Uttar Pradesh and look at the effect of polity size on public goods provision. They find that villages which form their own local government have better access to public goods and government welfare schemes relative to villages which are a part of larger local governments. At this point, it is important to highlight the considerable overlap between the context, data sources, and outcomes examined in their work and those discussed in this paper.

However, there is a key distinction that sets the two studies apart. In Narsimhan and Weaver (2023), the unit of analysis is the Gram Panchayat, whereas in this study, it is the district. The district administration is a purely bureaucratic entity whereas the GP is a publicly elected form of local self-government. Creation of a new, smaller GP involves a vertical devolution of political, financial, and administrative powers from the state to the new entity while new district formations entail a horizontal fragmentation of administrative units. An important channel through which smaller GP improve governance is by ensuring greater accountability and monitoring of electorally motivated GP members. This channel is weaker in the case of bureaucrats who are selected by an independent commission and answerable only to their higher-up officials. However, local politicians can apply pressure on bureaucrats and still keep them responsive to local needs.

The relevance of this crucial difference is reflected in the findings of the two papers where the former finds an unambiguously positive effect of smaller GPs since it captures the compound effect of administrative and political factors. This is supported by their results that suggest that the improvement in local outcomes is driven by greater civic engagement and difference in the quality of elected representatives. In this paper, I am able to isolate the effect of administrative decentralization which gives mixed results. I provide suggestive evidence that these results can be attributed to the lower distance between district HQ and GPs, lower ethnic fractionalization, and partly due to greater civic engagement.

A recent paper, Chaudhary and Iyer (2024), is similar to this one in its focus on the administrative dimension. In this study, the authors find a negative effect of devolution of administrative functions to GPs on child-health and education outcomes in the absence of concomitant devolution of control over functionaries or financial resources. However, in this paper, I study a different form of administrative decentralization that is generated from the creation of new districts which brings the district administration geographically closer to the grassroots level without devolution of new functions.

In sum, this paper contributes to the growing interest in exploring the impact of bringing administration closer to people through various channels, either by creating smaller units or by devolving functions to lower levels, on governance and development. It does so in the context of India but the lessons can be generalized to other developing economies with democratic institutions, and weak state capacity.

1.3 Institutional Background

1.3.1 Administrative System in India

India states are organized into a nested, multi-tiered administrative setup with district (formally known as revenue district) being the topmost administrative unit under the state. Districts are further divided into subdistricts[5], followed by blocks[6]

[5] Subdistricts are also referred to as Tehsils, Taluks, or Mandals in different states.

[6] Generally, a subdistrict consists of more than one block or parts of several blocks although in some states such as Goa, subdistricts and blocks are coterminous.

and (revenue) villages in the rural areas, and towns in the urban areas.

The district administration exercises authority over a wide-ranging set of revenue, judicial, executive, and development related matters for the area under its jurisdiction and shares these responsibilities, to varying extent, with the lower administrative bodies. While subdistricts are for the purpose of revenue collection and blocks are for planning and development purposes, both are accountable to the district administration. Subdistricts are further composed of villages and urban centers which are governed by locally elected bodies that are established pursuant to the 73rd and 74th amendment to the Indian constitution[7].

The district administration is headed by an Indian Administrative Service (IAS) officer from the national cadre of civil servants and are known as the District Collector[8]. The collector plays a pivotal role in the execution of government policies by ensuring supervision of and coordination among the different departments at the district level. The recruitment process of IAS officers is conducted by an independent constitutional body through a highly competitive examination and assigned across states based on a strict allocation rule[9]. Furthermore, the strength of each state cadre is determined by the central government in consultation with the state government and is ordinarily fixed for a period of five years[10].

[7]While similar elected bodies exist at the district and subdistrict level concurrent to the administrative bodies, the role of the former varies widely across states and is limited due to inadequate devolution of power, responsibilities, and finances.

[8]The district collector also holds various other titles based on the different roles that she assumes such as District Magistrate, and Deputy Commissioner.

[9]A similar process is followed at the state level for the recruitment of the other officers at the district, subdistrict and block level administration. This is done to shield the bureaucracy from political interference. In reality, however, the state government is still able to utilize its power to transfer officers across departments and districts to wield control over bureaucrats and influence their performance.

[10]As per The Indian Administrative Service (Cadre) Rules, 1954 which can be accessed here: https://dopt.gov.in/sites/default/files/Revised_AIS_Rule_Vol_II_IAS_Rule_01_0.pdf

Over time, the number of districts in the country has steadily gone up due to the reorganization of existing districts into newer, smaller districts. There were a total of 316 districts in the country as per the 1951 Census compared to 640 districts as per the latest 2011 Census. As of 21 June 2024, the reported total count stands at 785[11].

1.3.2 District Reorganization in Telangana

In 2014, the state of Telangana was created after bifurcating the existing Andhra Pradesh state. This followed decades of political movement and public demand for separate statehood which led to the enactment of the Andhra Pradesh Reorganization Bill in the Parliament of India. At the time of its formation, Telangana was the eleventh largest state in terms of area, twelfth largest in terms of population and comprised 10 districts making its districts much larger (around 11,200 sq km, 3,500,000 persons) compared to the average district in the country (4,855 sq km, 1,900,000 persons)[12].

While the constitution vests the power to create new states exclusively with the Parliament of India, the states hold the power to form new districts by altering the existing district boundaries. This can be achieved either through an executive order or by passing a law in the State Assembly. So, in accordance with Section 3 in the Telangana Districts (Formation) Act, 1974 and Telangana District (Formation) (Amendment) Act 2016, the government of Telangana carved out twenty one new districts in 2016 and two more in 2019. Figure 1.1 illustrates the change in district boundaries. This took the total number of districts from ten to thirty three, the

[11] As per the Integrated Government Online Directory website which may be accessed here: https://igod.gov.in/sg/district/states

[12] As per the 2011 Census of India data.

average population per district to 1,100,000 [13] and the average district size to around 3,400 sq km.

This move set the trend of district fragmentation as states such as Andhra Pradesh and Tamil Nadu followed suit. The state government' reasoning behind this policy measure can summed up by the then Chief Minister' quotes:

> Decentralization of administration will lead to decentralization of development.
>
> -Y.S. Jagan Mohan Reddy, CM Andhra Pradesh

The Telangana government set about the process of creating new districts in 2015 by conducting extensive stakeholder engagement. This included the constitution of a committee of secretaries from various departments, a cabinet sub-committee, a high-powered committee to consult with leaders of various political parties[14], and meetings with district collectors. The government also invited suggestions and objections from the general public by releasing a draft notification for the creation of new districts[15].

A task force was set up to formulate guidelines to restructure administrative departments by reviewing and redistributing the strength and jurisdiction in different cadres based on the size of the new district. The exigency of a fixed cadre strength

[13] Based on the state government's population projections.

[14] Although the draft notification for creation of new districts was backed by an all-party meeting held prior to its release, there were allegations that the new district boundaries were designed to appease the leaders of the ruling party and to restrict the clout of opposition leaders by splitting their constituency between multiple districts.

[15] The general public was given a 30-day window to file suggestions or lodge objections on the draft proposal through the Collector of the concerned district on the newly launched website www.newdistrictsformation.telangana.gov.in. In addition to receiving over one lakh objections, this period also witnessed a number of public agitations and protests with demands for a separate district or inclusion/exclusion from the proposed district. This is potential threat to my identification strategy based on regression discontinuity design if the number of cases of individual cases reallocated across the district boundaries was quite high. However, this does not seem to be the case.

in the short term[16] led to ad-hoc staffing decisions with some districts functioning without regular posts, disbandment or temporary addition of certain posts, and posting of junior IAS and IPS officers as district collectors and superintendents of police respectively with a senior IAS and IPS officer and a cabinet minister overseeing three or four districts each.

In addition to the manpower crunch, particular towns had to be identified which had the necessary infrastructure such as land, buildings to become the headquarters for the proposed new districts. A sum of Rs 100 crore was allocated to each new district to this end. Further, resources such as vehicles, furniture, files, computers etc. had to be redeployed to the new offices, Rs.1 crore was allocated to meet these expenses to each district, including to the existing districts.

The general guideline regarding reallocation of financial resources was to distribute funding under center and state government schemes between old and new districts based on some objective criteria such as district size and population. In the case of district-centric schemes like Backward Regions Grant Fund, funds would be allocated to one or the other, depending on whether either or both qualify.

However, the political and judicial infrastructure remained unchanged. The number and boundaries of state assembly and parliamentary constituencies remained unchanged. Local elected bodies were set-up at the new district level in 2019 when elections were held for the first time since district reorganization. However, the constituent jurisdictions at block level remained unchanged. New judicial districts, coterminus with the new districts, were launched and district courts set up much later

[16]The state also requested the center to allocate more IAS and IPS officers. Until then, the process of recruitment through the State Public Service Commission and Police Recruitment Board takes at least a couple of years.

in 2022.

1.3.3 Role of district administration in public programs

The district administration acts as the nodal agency for planning, budgeting, and implementation of public programs below the state level. In this section, I discuss the nature of district's involvement in further detail.

Planning: The focus on a decentralized approach to development planning is embedded in Article 243 of the Constitution. It mandates rural (panchayats) and urban (municipalities) local bodies to prepare their development plans in a participatory manner. It also directs districts to set-up planning committees responsible for consolidating the plans prepared by local bodies and blocks into a District Development Plan which would represent local needs and priorities on an annual basis. In practice, however, due to limited local technical expertise and uncertainty surrounding resource allocation at the local level[17], development planning largely remains a district-level exercise. For instance, although planning of works under NREGS follows a bottom-up planning approach, district prioritizes the type of works to be undertaken based on its total allocation and accordingly finalizes block wise action plan[18] of the district.

Funding: Generally, allocation of funds to each tier of the sub-government is determined by a normative formula that takes into account factors such as area, population as well as specific socio-economic or infrastructure indicators directly targeted by the scheme such as population (total or share) of poor, backward castes, homeless, unelectrified etc. This lack of flexibility if reflected in the panchayat development

[17] As per 'Catalysing Actions for District Development Planning by Consolidating Local Priorities' (2019) report by Society for Participatory Research in Asia

[18] The block administration follows a similar approach in drafting panchayat-level plans.

plans where demand for funds is often based on previously allocated figures with slight upward adjustment. In practice, there is significant discretion in how the district administration reallocates resources to the blocks and villages within its jurisdiction which leaves scope for lower levels to influence decisions through lobbying.

Execution: The main responsibility of executing schemes at the grassroots level lies with the panchayats. For instance, under NREGS, Panchayats are responsible for executing at least 50% of the works. Panchayats are responsible for the identification of beneficiaries as per official guidelines under individually targeted programs as well as overseeing the day-to-day operation of the scheme. District administration's role is to monitor and supervise the scheme implementation, conduct regular audits, and facilitate training and capacity building of various stakeholders. Although, the district may also be more directly involved in the scheme implementation through its line departments such as the Public Works Department or Irrigation Department as is the case under NRGES (Sukhtankar, 2017).

1.4 Conceptual Framework

In this section, I outline the theoretical arguments both for and against government fragmentation, and explore how each of these could manifest in the context of district re-organization in Telangana.

Drawing on Alesina and Spolaore (1997), I posit that the policy decision of fragmentation entails a fundamental trade-off between economies of scale and heterogeneity. Large sub-national units enjoy the benefits of economies of scale in the provision of public goods and services to its people. Additionally, the establishment and management of additional sub-national units lead to increased fixed and operating costs. Further, decentralized provisioning results in inefficiency in presence of externalities and spillovers across jurisdictional boundaries (Besley and Coate (2003)).

At the same time, individuals in larger units are less likely to be homogeneous in their preferences for local goods, resulting in a greater gap between the public choice and the preferred choice of the average individual. On the other hand, decentralized provision of public goods by utilizing greater information of local needs (F.A.Hayek (1945); Tiebout (1956))) and by promoting inter-jurisdictional and yardstick competition (Oates (1999); Besley and Case (1995)) results in more tailored and optimal policies. Customization encourages experimentation which leads to the adoption of best practices across jurisdictions. However, yardstick competition does not facilitate bargaining and could make policy coordination between different jurisdictions difficult (Qian (1994)).

Using insights from the political economy of decentralization literature (Mookherjee (2015)), another plausible channel through which district re-organization may impact local outcomes is by altering the behavior of government and political agents. By bringing government closer to the people, fragmentation allowing closer monitoring of the actions of officials (Crémer et al. (1996); Seabright (1996)) thereby making them more accountable if their rewards or promotion depends on their reputation and performance. More sub-national units might further allow for the entry of new political participants (Myerson (2014)). Inter-jurisdiction competition also limits the extent of corruption and rent seeking (Edwards and Keen (1996)). At the same time, reduced distance, geographic and social, between government and local actors could result in higher level of corruption and elite capture especially if it strengthens patronage networks (Prud'homme (1995b); Bardhan and Mookherjee (2000a)).

The overall effect would depend on the relative strength of the competing forces along with the strength of state capacity and quality of democratic institutions (Bardhan (2002)). I elaborate on these in the context of Telangana and discuss their potential role in determining the impact of district re-organization in the state.

First, districts form the third tier in India's federal administrative set-up. Unlike decentralization of power to the village councils in India, which has been extensively studied, district re-organization does not involve devolution of specific functions or new powers to the districts. Policies are formulated by the federal and state legislative assemblies. The district administration is tasked with implementing these policies in accordance with official, objective guidelines. In practice, however, the officer-in-charge at the district level, known as the district collector, exercises considerable discretion in the distribution of public goods and services to different jurisdictions within the district based on local needs. Thus, considering the weak state capacity in developing countries, district reorganization has the potential to foster greater development by bringing district administration closer, in terms of both information and physical proximity, to previously far flung and under-served areas.

Second, district administration is run by independently appointed bureaucratic officers instead of publicly elected representatives. These bureaucrats are answerable to higher-up officials and politicians who exert influence over their transfers and postings. They are not directly accountable to the people. However, since the elected bodies below the district administration like the zilla parishad and the panchayat samiti do not enjoy a lot of powers, members of the public often have to approach the district administration to lobby for goods and services, local and private, and for grievance redressal. Additionally, the public may also urge their local politicians to apply pressure on the district administration. While the number and the boundary of political constituencies remained unchanged, district reorganization leads to smaller districts with fewer number of local politicians per district. Further, new districts led to the creation of new posts for local political party presidents and office bearers giving rise to new political leadership. Therefore, creating new districts can improve implementation of government schemes by making district administration more accessible and responsive to the people, and by attenuating the extent of common agency problem (Gulzar and Pasquale (2017)).

Third, district re-organization involves reallocation of fiscal resources among a larger number of districts. Districts in India generally rely heavily on funds transferred from the federal and state government for the implementation of various schemes and have limited scope for raising and employing their own finances. In case of creation of new districts, funding under different schemes either gets apportioned among old and new districts based on some objective criterion such as the population share of targeted beneficiaries, or is directed to either one or both depending on whether they qualify for scheme benefits like under the Backwards Regions Grant Fund federal scheme which channels funds into designated districts with gaps in local infrastructure. In case of the former, expenditure under the scheme could potentially remain unchanged while in case of latter, it multiplies. Irrespective, the total cost of supplying the same level of goods and services goes up owing to higher administrative costs.

Fourth, creation of new districts leads to multiplication of posts and necessitates filling up many positions by redeployment of existing staff, and hiring of new employees. While new hiring adds to the operational costs, it also creates employment opportunities. Additionally, towns with the new district headquarters can act as growth centers as households and businesses flock to the improved infrastructure facilities, public goods and services set up under various district-specific schemes such as agricultural research and assistance center, district hospital etc. Together, these two forces could result in greater economic growth in the new districts. In the short-run, however, there might be shortage of manpower in key posts, such as the district collector, due to stringent rules around the recruitment and cadre strength of civil servants. Further, if the district headquarter is set up in an existing town, as was the case in Telangana, the district would not benefit from new infrastructure development.

Finally, the process of re-drawing district lines in Telangana witnessed massive protests by the public demanding creation of new districts based on social, historical, geographic and infrastructural factors. Therefore, public participation in the process led to the creation of districts that are more homogeneous in preferences and ethnicity which could result in a more optimal provision of public goods and services. At the same time, there's some anecdotal evidence that suggests that the needs of specific districts are being overlooked due to their tribal identity (Hans India (2020)).

1.5 Data

To examine the effect of district reorganization on local developmental outcomes, I construct a village-level dataset by combining remote sensing data, administrative data, and political data from various sources. This section describes each dataset used in this paper in further detail.

1.5.1 Main Data

National Rural Employment Guarantee Scheme I collect annual, village-cluster i.e., Gram Panchayat (GP) level data on the scheme implementation from the Mahatma Gandhi National Employment Guarantee Act (MGNREGA) public portal for the period between 2014-2015 to 2022-2023. I then assign GP outcomes to their constituent villages. To do this, I match NREGS GPs to their villages by using the GP-village mapping available on the Local Government Directory (LGD) website and fuzzy matching on GP names[19]. Some of the NREGS outcomes I looked at include the demand for work, number of days worked, wages disbursed, number of vendors, and delay in compensation.

Mission Antyodaya Adopted in 2017-18 as a convergence framework, data collected under Mission Antyodaya (MA) contains detailed information on village infrastructure and services, and the number of beneficiaries under various government welfare programs. This data is collected from the relevant service providers and updated annually using the 2011 census as the baseline. For my analysis, I use the 2019-20 data which is available publicly, and I focus on infrastructure indicators with 2011 census counterparts, and number of beneficiaries under schemes introduced after district re-organization.

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[19] I use the mapping for the years 2016 and 2021 to account for the creation of new GPs and reassignment of villages across GPs over time.

System TS-iPASS was launched in 2016 and allows investors to obtain the required permissions to establish manufacturing and service industries in the state within stipulated time frame through a single window online system. I use village-level administrative data on applications received under TS-iPASS during the period between 2017-18 to 2023-24 including the proposed level of financial investment and employment.

Nightlights I download the latest version of the annual time series Visible and Infrared Imaging Suite (VIIRS) nighttime lights data by Earth Observation Group. This series has been produced from monthly cloud-free average radiance grids from 2012 to 2020. Therefore, a value of zero does not mean that no lights were observed. This newly introduced version is an improvement over the previously available DMSP-OLS data that has been widely relied on the existing literature. In particular, it has been shown to be a better proxy of GDP at a higher level of spatial granularity and low-density areas (Gibson et al., 2021) which is a key element of the spatial RD design employed in this paper.

1.5.2 Additional Data

2011 Census of India To test for pre-treatment balance, I obtain 2011 Census of India village-level data from Socioeconomic High-resolution Rural-Urban Geographic Data set (SHRUG). In particular, I use information provided in the Population Census Abstract on population figures disaggregated by caste, gender, literacy, and worker class. Further, I include data from the Village Amenities which details information on village level infrastructure such as schools and roads, and civic amenities such as drinking water source.

GP elections To explore the effect of district re-organization on local political participation, I look at GP head (or Sarpanch) elections data for the year 2019 from Telangana State Election Commission. This data includes GP-candidate-level information on the candidates' names, votes received, GP reservation status, and total voters.

GIS For my main results, I obtain GIS data on village boundaries from SHRUG, historical district boundaries for the year 2011 from ML InfoMap, and new district boundaries from Survey of India. I obtain geocoordinates for the old district headquarters from Survey of India and for the new district HQs from Google maps. While the historic district assignment of a village is based on its corresponding 2011 district code, the new assignment is based on whether the village centroid is located within the boundaries of the district with the old HQ or the newly created district. Further, distance from the village centroid to the new district boundary is calculated using QGIS to be used as the regression discontinuity running variable. Finally, I use the shapefile for assembly constituencies in Telangana provided by the Chief Electoral Officer, Telangana on Open Data Telangana website.

Combining datasets When available, I merge datasets on 2011 Census administrative unit codes. For instance, since SHRUG village shapefile included census codes, I combined Mission Antyodaya data with village spatial data using village id. However, in the absence of a common unique identifier, combining different datasets is a complicated exercise that relies extensively on fuzzy name-matching. For instance, GP names are spelled differently in NREGS data as compared to LGD data. As result, GP-village mapping required fuzzy name-matching on GP names.

1.6 Empirical Strategy

In order to measure the effect of being located in a newly created district, I can estimate a straightforward difference-in-differences model using the full sample of villages. In this case, villages in the old district would act as the control group for the villages in the new district. However, in order to estimate any causal effect, new and old district villages' outcomes should satisfy the main identifying assumption of parallel pre-trends. This is difficult to test in the present context due to the lack of availability of relevant data for a sufficient number of pre-policy years. Further, villages in the old district may not be comparable to villages in the new districts.

So, for the purpose of my analysis, I employ a spatial RD design which compares villages that are close to the border between the old district[20] and the adjoining new district. I illustrate my empirical strategy in Figure 1.2. New district villages at the border are reliable counterfactual for the old district villages because they were historically part of the same district and shared similar underlying conditions before the policy change. To test if this holds, I conduct a balance test using pre-treatment data on geographical and demographic covariates and present the results from this exercise in the next section. The baseline spatial regression discontinuity equation takes the following form:

$$Y_{v,g,d,b} = \beta_1 NewHq_d + f(Location_v) + \beta_2 X_v + \delta_b + \epsilon_{v,g,d,b} \tag{1.1}$$

where $Y_{v,g,d,b}$ is the outcome of interest for village v in GP g located in dis-

[20] I use "parent district" to refer to pre-policy district boundaries and "old district" to refer to post-policy district boundary that contains the parent district HQ

trict d, along boundary b between district d and the adjoining district. These include NREGA outcomes, beneficiaries under different government schemes, village infrastructure index, and industrial investment and employment. $NewHq_d$ is the binary treatment variable. It takes the value 1 if the village belongs to a new district d and 0 if it belongs to an old district. The main coefficient of interest if β_1 which captures the effect of being located in a newly created district.

$f(Location_v$ is the RD polynomial that controls for smooth functions of the geographic location of the village. Following Dell (2010), I control for a two-dimensional local linear polynomial in the village centroid's latitude and longitude. This absorbs any smooth trends in outcomes at the border. Since there is no well-accepted optimal bandwidth for a two-dimensional RD setting (Dell and Olken, 2017), I restrict my sample to villages within 10 kilometers of each old-new district boundary. To test for the robustness of my results, I also estimate my results under alternate specifications such as using different bandwidths, a quadratic polynomial in latitude and longitude, and a global polynomial approach by controlling for higher order of latitude-longitude polynomial (cubic or quartic) and the full sample of villages.

X_v refers to the set of village level controls including village area, total population, proportion of illiterate population, and the proportion of population engaged in cultivation. The area and population control for the village size, I include the latter two variables (as discussed in the next section).

δ_b is the boundary fixed effects where b is the closest old-new boundary to the village v. This ensures that I'm comparing villages in close geographic proximity of each other. In cases where I have multiple years of pre or post data such as in the case of NREGA, I also include year fixed effects.

$\epsilon_{v,g,d,b}$ is the error term. Following Abadie et al. (2022), I cluster my standard errors at the child-district level to allow for potential clustering of the errors within post-policy district jurisdiction.

1.6.1 Balance Test

A key assumption of a valid RD design requires that the distribution of all factors (observed and unobserved), other than the treatment, is continuous on either side of the threshold. In this context, this is crucial as it ensures that villages on either side of the old-new district boundary are sufficiently similar to consider district assignment to be as good as random and allows us to interpret any difference in post-policy outcome as the treatment effect.

As a result, the main threat to the identification in this setting would be if the new boundaries and the timing of district reorganization were endogenous. Empirical evidence suggests that new administrative units are often targeted to ethnically, politically, and economically marginalized areas (Grossman and Lewis, 2014) and given the democratic nature of the district reorganization process in Telangana described in Section 2.2, the concern is valid.

To mitigate this concern, I look at the pre-treatment difference between new and old district using village level census data from the 2011 Indian Census. For this purpose, I have selected a set of demographic variables that are highly correlated with the eligibility for a number of government welfare and development schemes such as NREGA (Deininger and Liu, 2019). These include (1) the proportion of socio-economically disadvantaged population groups such as the Scheduled Castes and the Scheduled Tribes, (2) proportion of illiterate population, (3) proportion of population that is engaged in cultivation or agricultural labor, and (4) proportion of population that is only marginally attached to the labor force. Further, I also include (5) mean elevation to account for geographical differences in case the new district borders are delineated along natural barriers such as a mountain range. As shown in Table **??**, I find little imbalance between old and new district villages along these covariates. The proportion of illiterate and the proportion of cultivators is higher in new district villages by 1.5pp and 2.6pp respectively. These differences are small, nevertheless, I include them as a control in my regressions.

Further, wherever feasible as in the case of NREGA, I estimate the baseline spatial RD equation using pre-policy outcomes data to check whether the old and new district boundary villages had similar initial outcome levels. As shown in Figure 1.3, the point estimates for β_1 are small and insignificant. Finally, where pre-policy outcome data is unavailable, I adopt the following two approaches: (1) calculate equivalent measures for the pre period using supplementary data set which provides information on some proxies that trend in the same way as my outcome of interest, and (2) I restrict my attention to government schemes that were launched after the policy change so that the pre-treatment difference is zero by definition. I will discuss this in further detail in the relevant results section.

1.7 Results

1.7.1 National Rural Employment Guarantee Scheme

I begin by examining the results for National Rural Employment Guarantee Scheme (NREGS) using administrative data for the period between 2014-2022. My main outcome of interest is the number of person-days of work generated under the scheme. Person-days refers to the total number of days worked by a person registered under the scheme. I also include other variables such as the number of households employed, the number of persons who demanded work, number of persons offered work, amount of wages disbursed into workers' bank or post office accounts, total expenditure under the scheme, and the the delay in compensation of wages.

The main results are presented in Table 1.1. Columns (1)-(2) show pre-treatment balance on the outcome variable while columns (3)-(4) show the treatment effect. I find that the number of households employed and number of person-days of work generated under NREGS during 2017-2022 is higher by 9.8% and 13.6% respectively in the new district villages relative to the old district villages. I find no evidence of any imbalance at the boundary at the baseline. These results are robust to alternative empirical specifications including dependent variable normalized by village population (refer to Table 1.9) and also higher degree of polynomial in the village centroid's coordinates (refer to Table 1.10).

To explore the dynamics of the effect, I also run the baseline specification for each year separately. These estimates for each year are presented in Table 1.2 and depicted in Figure 1.3. One of the limitations of this analysis is that I am only able to look at only two years before the policy change due to the lack of availability of relevant data for earlier years. Nonetheless, I find that the positive treatment effect is highest in 2017, the year immediately after the policy change, and tapers off over time and becomes insignificant during the last year included in my sample.

1.7.2 Mission Antyodaya

In this section, I look at the differential access to village-level infrastructure and government welfare schemes between old and new district villages using 2019 Mission Antyodaya (MA) data. Two more rounds of MA survey were conducted before the one in 2019, however, the 2019 round was the first round to have a comprehensive coverage of all the GPs[21] in the country. So, I cannot use data from earlier rounds to establish that villages within 10km of the boundary of the old district are comparable to each other. I deal with this issue in the following two ways: (1) MA collects information on village amenities that is similar to that collected under the Census of India's Town/Village Directories. This allows me to test for pre-treatment balance along this dimension at the threshold, and (2) I focus exclusively on welfare schemes that were launched after the policy change in 2016 so that any difference in the 2019 round can be ascribed to difference in the characteristics of the splinter districts.

I begin with constructing a composite measure of the level of village infrastructure by taking the average of a number of individual facility indicator variables. These include availability of (1) schools, government degree college, vocational education center, library, recreational center; (2) piped tap water, irrigation, drainage, waste disposal system; (3) post office, ATM, bank, telephone, common service center; (4) electricity, all-weather road, bus stop, railway station; and (5) market, farmers' collective, public distribution system. The RD estimates using both 2011 Census and 2020 MA data are presented in Table 1.3. I find no statistical difference in the level of local infrastructure between the old and new district villages.

[21] Although GPs are the focal point for the convergence and accountability framework under Mission Antyodaya, it is important to note that it is a village-level survey.

Next, I examine access to benefits under different individually targeted central government sponsored welfare schemes. Since I'm looking at a large number of outcomes, I create a standardized index following (Schwab et al., 2020)[22] to deal with concerns regarding multiple hypothesis testing. The schemes included in the index are: (1) Saubhagya or Pradhan Mantri Sahaj Bijli Har Ghar Yojana which provides electricity connections to rural households; (2) Pradhan Mantri Ujjwala Yojana (PMUY) which provides LPG cooking fuel cylinder to rural households; (3) KCR Kit[23] which provides cash transfers to pregnant and lactating mothers; (4) Pradhan Mantri Jan Arogya Yojana (PMJAY) is public health insurance scheme; (5) Pradhan Mantri Kisan Pension Yojana (PMKPY) is a farmer pension scheme; (6) Pradhan Mantri Fasal Bima Yojana (PMFBY) is a crop insurance scheme; (7) Organic' measures the number of farmers who adopted organic farming during the survey year[24]; (8) Rashtriya Gram Swaraj Abhiyan (RGSA) which a capacity building and training scheme for rural elected representatives.

I run the main RD regression on the beneficiary index and each individual scheme separately. These results are presented in Table 1.4. Column (1) finds that new district villages have a 0.106 standard deviation lower value of this index relative to the old district villages. Looking at the remaining columns (2)-(9) of Table 1.4, I observe that the effect on beneficiary index is driven by two schemes in particular, namely, KCR kit and RGSA which witness lower rate of beneficiaries by 2.6 pp and

[22]The procedure follows a GLS weighting procedure as described in Anderson (2008)

[23]MA collects information on the number of beneficiaries under Pradhan Mantri Matru Vandana Yojana (PMMVY). However, since Telangana was already implementing a similar scheme namely KCR, it chose to not implement PMMVY so the data collected under PMMVY under MA for Telangana can be ascribed to KCR Kit scheme.

[24]There are a number of centrally sponsored schemes that promote organic farming such as Paramparagat Krishi Vikas Yojana (PKVY)

4.4 pp in the new district villages.

1.7.3 TS-iPASS

Next, I look at the whether new districts succeeded in attracting new investment as the policymakers has hoped. I use the data on requests for permission received under TS-iPASS as a proxy for industrial investment. Before proceeding, I test for pre-policy balance between the old and new district villages at the border by comparing the change in per capita employment and number of establishments using village-level Economic Census data for 2005 and 2013. These results are presented in Table 1.11 which indicate that the null no significant difference cannot be rejected.

Table 1.5 reports the RD estimate based using TS-iPASS data. Column (1) looks at the probability that a village receives at least one investment application while columns (2) and (3) look at the extent of investment and employment generated in a village respectively during this period. The dependent variables are log transformed (after adding a small constant to account for zeros) so the coefficients can be interpreted as the percentage difference in outcomes between old and new district villages. Further, I also interact my main independent variable NewHq with an indicator variable for the village being within 20 km of its district HQ. This allows me to study the heterogeneity of the treatment effect by distance to district HQ.

I find that, firstly, the coefficient on NewHq is negative and significant in all three columns. This suggests a negative effect of district reorganization on attracting new investment and employment opportunities to new district villages. The likelihood of attracting a certification application under TS-iPASS is lower by 7.8pp, the amount of proposed investment is lower by 41.4pp, and employment by 30.9pp.

Secondly, villages within 20km of the district HQ are more likely to receive investment proposal than villages that are farther away. This result also holds for the size of investment and employment. The coefficient size on the interaction term is positive, significant in all three columns. This result is consistent with the literature that documents negative effects of distance to district administration on local economic outcomes (Asher et al., 2018). Finally, since the positive coefficient on the interaction term is larger than the negative coefficient on NewHq, it implies that overall impact on villages closer to the district HQ in new districts relative to the old district villages is positive in term of probability and proposed level of investment.

1.7.4 Nighttime Lights

Nighttime lights are commonly used to study the effect of shocks or policy changes on local economic activity. Establishment of new district headquarters can turn towns into growth centers. In such a case, one would expect to see a positive impact on nightlights. The results on the effect of district reorganization on nightlights are presented in Table 1.6. I find no significant difference in the nightlights intensity between old and new district villages within 10km of the new district boundaries. These results are not surprising since reports suggest that well-established towns with pre-existing infrastructure were chosen as the location for new district headquarter.

1.8 Mechanisms

The existing literature has put forth several mechanisms that help explain the effect of decentralization on public service delivery. In this section, I consider a few to see if any of these are supported in this context. The three main mechanisms that I test for include: (1) distance to the headquarter, (2) change in district caste composition, and (3) civic participation. These results allow me to better understand the driving force behind my main results and also with their interpretation.

1.8.1 Distance to Headquarter

One of the ways administrative unit fragmentation can improve the delivery of public goods and services is by bringing the administration closer to the people. Lower distance between the citizens and the bureaucracy can have many advantages on both the supply and demand side of public good provision. On the supply side, it can lead to better information about local needs, lower cost of supplying public goods and monitoring their quality, better coordination between different tiers of bureaucrats (Faguet, 2004; Asher et al., 2018; Bozcaga, 2020). On the demand side, it can improve community-based monitoring of bureaucrats, and improved public access to avenues for lobbying and grievance redressal (Olken, 2007).

To test for the role of distance to district headquarter, I run the baseline RD equation for person-days along with control for distance to district headquarter and an interaction term between the treatment variable *DistanceHq* and an indicator variable for if the village's distance to district HQ is less than 30km. The results are presented in Table 1.7. Column (1) looks at the pre-policy period (2014-2016) and column (2) provides estimates for the post policy period (2017-2022). *DistanceHq* is based on the distance to the relevant HQ in each period. So, for old district villages, *DistanceHq* is same for the pre and the post period. However, for new district villages, *DistanceHq* in post is more likely to be 1 as distance to HQ falls. In column (2), I find that the interaction term is positive and significant. This shows that main RD result for person-days is being driven by new district villages that are within 30km of their new HQ. There is no relationship between distance to HQ and person-days for the new district villages relative to the old district villages in the pre-period[25]. I find similar results using TS-iPASS data for villages within 20km of the new district HQ(reported in Table 1.5. The sensitivity of these results with respect to the choice of distance threshold reflects the suggestive nature of the evidence on the role of distance to HQ and not a prescriptive estimate of the optimal distance to administrative HQ.

These results suggest that by bringing administration closer to people, district reorganization can have a positive effect on public service delivery.

1.8.2 District's Caste Composition

District reorganization often leads to the creation of more homogeneous subnational units in formerly ethnic minority areas as a form patronage (Green, 2010; Hassan, 2016). The literature on decentralization recognizes the trade-off between heterogeneity and economies of scale (Alesina et al., 2004) in determining optimal jurisdiction size. Differences along dimensions such as ethnicity, race, or caste can make heterogeneous populations are more costly to serve if these differences translate into difference in preferences for public goods. To test this claim, I look at whether the treatment effect in stronger in new districts with lower ethnic fractionalization post district reorganization.

Column (1) in Table 1.8 reports the results on the heterogeneity of effect on NREGS person-days by change in the Herfindahl–Hirschman index of caste concen-

[25] This is the basic assumption of the spatial RD design.

tration. Here, ''hhi_dec' is a dummy that takes the value 1 if the value of caste-based HHI decreases after district reorganization. The interaction term between new district and ''hhi_dec' is positive and significant. This implies that there is a greater effect in the new district villages that experienced a decrease in the extent of caste concentration in their district.

1.8.3 Civic Participation

Decentralization can also encourage citizen participation by making the government more accessible to people. This mechanism might be even stronger as district reorganization is often a political response to growing demand and collective action for creation of separate district by discontented electorate. To test if this holds in my context, I look at the rate of voter turnout in local rural body or GP elections. GPs play a pivotal role in the implementation of NREGS at the village level from planning works to lobbying local politicians and bureaucrats for greater budgetary allocations.

Column (2) in Table 1.8 shows the heterogeneity of the treatment effect by 2019 GP election voter turnout. ''sh_vote50' is a binary variable that takes the value 1 if the rate of voter turnout in greater than 50%. The interaction term is positive and significant between the NewHq dummy and ''sh_vote50' which implies that greater person-days of work is generated in GPs with higher voter voter turnout in new district villages. These results lend support to the civic participation channel.

1.9 Discussion

One challenge in interpreting NREGS results is in distinguishing if the effect is driven by better scheme implementation i.e., greater supply or by greater demand or both. Previous studies on the scheme have found that even though NREGS is a demand-driven scheme, there is under-provision of work under NREGS due to budgetary constrains, weak local administrative capacity and low willingness to undertake projects (Dutta et al., 2012; Witsoe, 2014; Muralidharan et al., 2016). Thus, there is reason to believe that the results in Table 1.1 are driven by improved implementation of the scheme. Even in the scenario where there is an increase in demand for work under NREGS, these results suggest that it is being met by the administration.

There might also be concerns regarding the reliability of administrative data and the worker numbers being artificially inflated in the official records. One way to test for this is to look at the amount of wages disbursed through worker bank account or post office. This ensures that the person-days numbers are not on account of "ghost workers" that only exist on paper. These results are presented in Table 1.13. This shows proportionate increase in the amount of wages disbursed in new district villages corresponding to the increase in person-days by 13.1pp.

Turning to the results based on MA survey data, I see negative differential in the rate of beneficiaries under maternal cash transfer and RGSA. These schemes differ from the other individually targeted welfare schemes included in the beneficiary index in two ways. First, PMMVY was not implemented in Telangana due to the presence of a similar state level scheme called KCR Kit Scheme. Second, the extent and the nature of the role of the district administration in its implementation is greater than the other schemes.

For instance, under KCR kit, the beneficiary application must go through several layers of approval including the Deputy District Health and Medical Officer and the Finance Department before benefits are transferred to the beneficiary account. On the other hand, PMMVY transfers funds directly to the state's dedicated escrow account and from there to the beneficiary account after approval from the state nodal officer. This explanation would be consistent with Banerjee et al. (2020) who find that one of the ways to reduce leakages under public programs is to cut down the number of tiers in the fund transfer chain[26]. Likewise, RGSA is a training scheme for elected representatives and is operationalized at district level training institutes which likely did not exist at the time of the survey. This would have necessitated alternative arrangements to be made to resolve this issue. Therefore, the lower rate of beneficiaries in the new districts likely captures the disruptive effect of district reorganization on schemes with top-down implementation. However, without additional information it is difficult to precisely identify the underlying mechanism driving this result.

Further, I see no positive effect on the level of infrastructure in new district villages. This can be attributed to the long-term nature of planning and execution of these public goods which would not have been realized for the period between district reorganization in 2016 and the time of the 2019 MA survey. The same reasoning likely applies to the absence of significant difference in the nightlights between old and new district villages.

Finally, I find a negative effect on the number of applications for new investment

[26]https://www.aeaweb.org/articles?id=10.1257/app.20180302

received under TS-iPASS for new district villages, particularly those farther away from the district headquarters. One explanation could be that the process of setting up of industrial units involves navigating a significant amount of red tape. This process may become even more challenging in a district undergoing major restructuring, which could be deter potential investors. However, this negative effect may be offset by the availability of improved infrastructure in the towns where the district headquarters are situated, which would account for the positive effect in nearby villages.

The main takeaway from the these results is that district reorganization had mixed effect on local development and access to public goods and services. There is evidence of positive impact on a NREGA, a scheme with bottom-up implementation, particularly in villages closer to the new district HQ, high rate of voter turnout in local elections, and lower ethnic fractionalization. These factors likely facilitate collective action and lobbying of district administration for NREGA benefits. However, district reorganization has no effect on nightlights, local infrastructure, and a negative effect on new applications for industrial licenses, sectors with top-down implementation. Therefore, the direction of the impact of this policy change depends on the type of public good or service under consideration, and the nature and the extent of district administration's involvement.

1.10 Conclusion

Administrative unit proliferation emerged a popular policy tool among countries implementing decentralization reforms in the 1990s and is witnessing a resurgence in importance as populations grow in size and administration of existing units becomes unwieldy. Despite its popularity, the relationship between creating new sub-national units and development outcomes has remained ambiguous, both theoretically and empirically. In this paper, I find that that new administrative units can improve public service delivery especially under programs that adopt a bottom-up approach in planning and implementation.

While my data does not allow me to rigorously identify the channel through which the district reorganization impacts public service delivery, there is some suggestive evidence that points to the role of distance to district headquarter and the level of collective action. I test for some other plausible mechanisms that have been offered in the decentralization literature, but do not find support for them in my data and in this context. Future work should focus on alternate channels that I could not explore here, such as changes in allocation of finances, staff vacancy and bureaucratic workload, and the extent of corruption. Better understanding of the underlying mechanism through which administrative unit proliferation can affect public service delivery will help us better inform public policy aimed at improving governance and welfare.

Figure 1.1: District Reorganization in Telangana

Notes: This figures shows how district boundaries were re-drawn in Telangana. In this map, the original "Parent" districts are color coded while the dark black lines demarcate the "splinter" district boundaries.

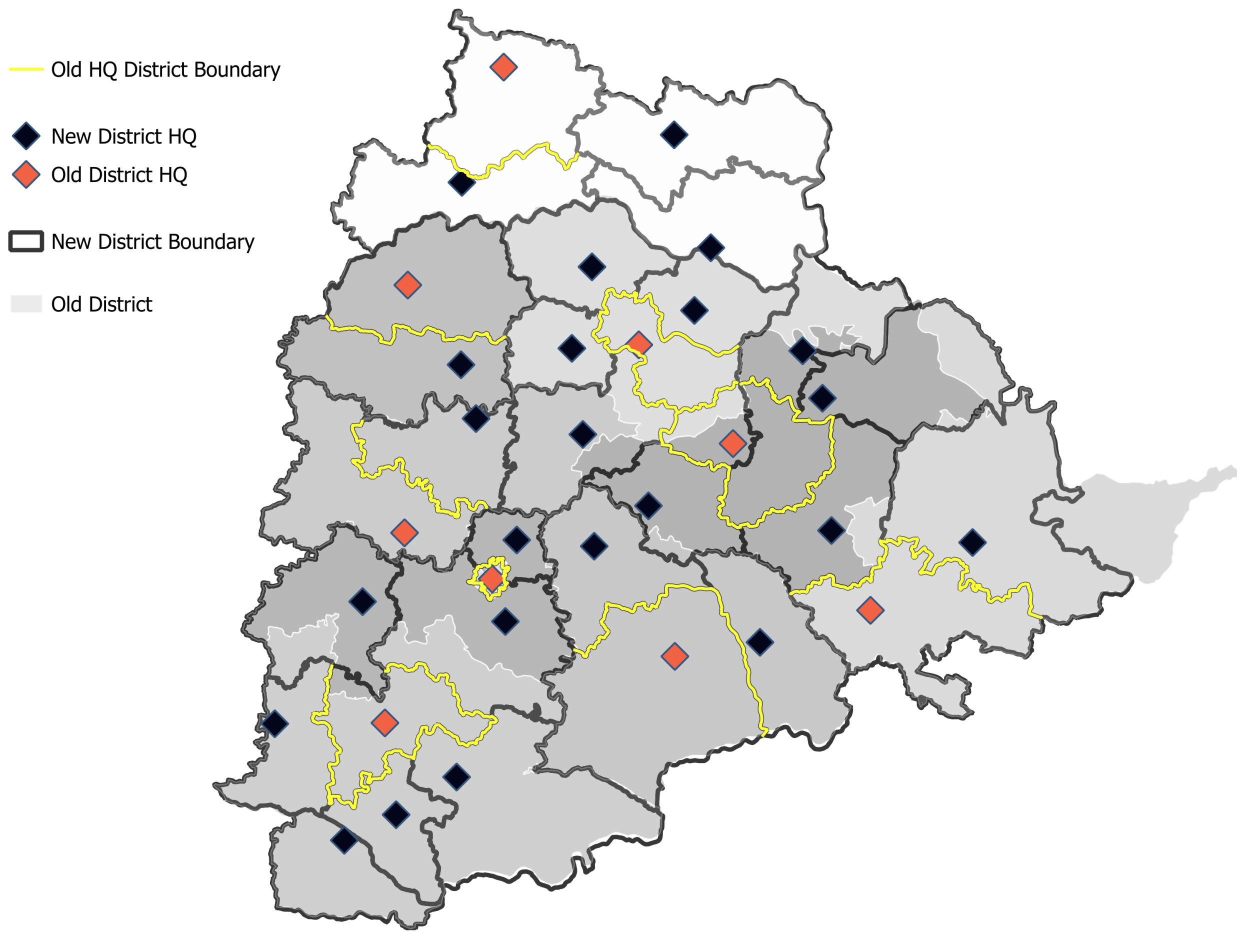

Figure 1.2: Spatial RD empirical design

Notes: This figures shows how district boundaries were re-drawn in Telangana. The original old districts are color coded while the dark black lines demarcate the new district boundaries. It also illustrates my spatial RD empirical strategy. The yellow line represents the border between the old district (with the parent district HQ) and the adjoining new district.

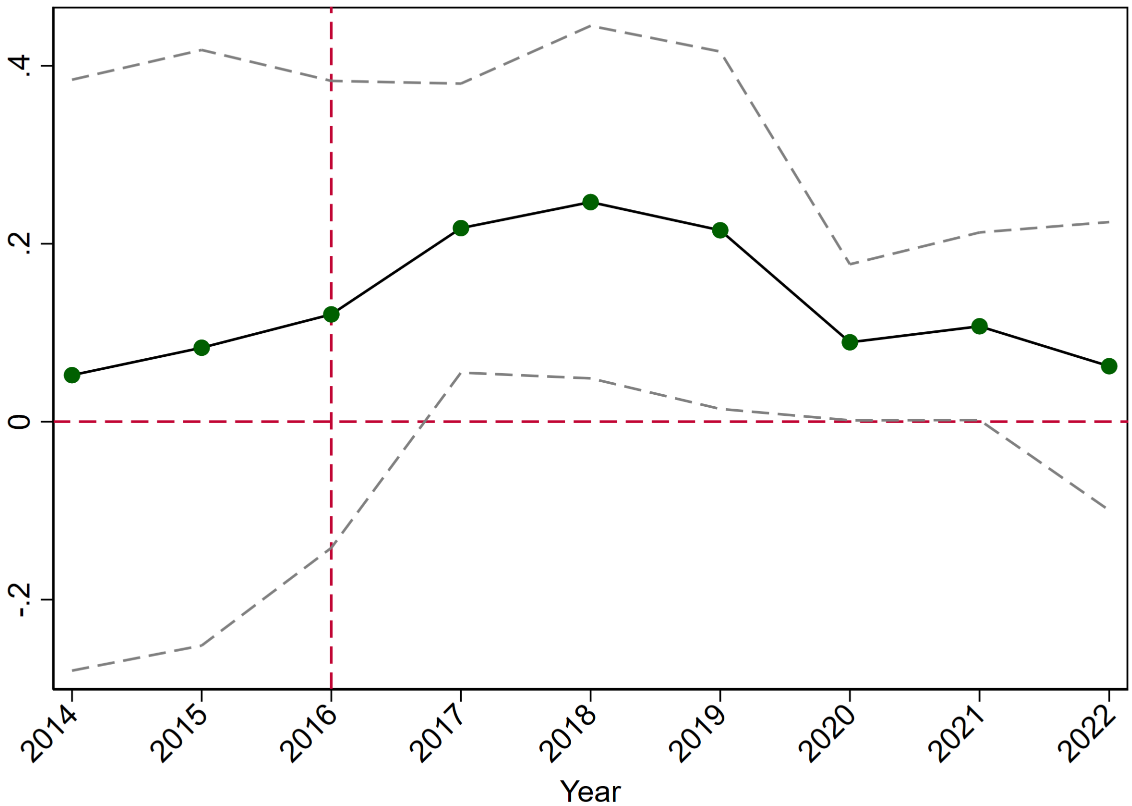

Figure 1.3: Dynamics of the effects on NREGA

Notes: The solid line plots the point estimates from year-wise RD regression and the dash lines denote 95 percent confidence interval. All regressions include two-dimensional local linear geographic controls, village controls along with boundary fixed effects. The sample includes villages within a 10 km bandwidth of district boundary. The vertical line at 2016 is for FY 2016-17 when the policy change took place.

	2014-2016		2017-2022	
	HHs emp. (1)	Person-days (2)	HHs emp. (3)	Person-days (4)
NewHq	0.080	0.085	0.098**	0.136**
	[0.094]	[0.150]	[0.041]	[0.058]
Mean dep. var	5.395	8.998	5.283	8.966
Observations	9,219	9,219	21,906	21,906
R-sq	0.376	0.360	0.270	0.237

Notes: The dependent variable is ln(1+ outcome). The unit of observation is at GP-village level. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls along with boundary and year fixed effects. I also include village controls for area, total population, proportion of population that is illiterate, proportion of cultivators. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.1: Spatial RD estimates of effect on NREGA

	Log(1 + Person-days)				
	(1)	(2)	(3)	(4)	(5)
	2014	2015	2016	2017	2018
NewHq	0.052	0.083	0.121	0.218**	0.247**
	[0.163]	[0.164]	[0.128]	[0.080]	[0.097]
Mean dep. var	8.843	9.208	8.943	8.990	9.038
Observations	3,073	3,073	3,073	3,050	3,050
R-sq	0.375	0.361	0.353	0.343	0.387
	2019	2020	2021	2022	
NewHq	0.215**	0.089**	0.107**	0.062	
	[0.098]	[0.043]	[0.052]	[0.080]	
Mean dep. var	8.856	9.080	8.987	8.842	
Observations	3,050	4,252	4,252	4,252	
R-sq	0.349	0.117	0.136	0.140	

Notes: The dependent variable is ln(1+ persons-days). The unit of observation is at GP-village level so N changes over time due to suspension of old GPs, creation of new GPs, and/or reassignment of villages across GPs. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls, village controls along with boundary fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.2: Dynamics of the effects on NREGA

	2011 Census (1)	2020 MA (2)
NewHq	-0.004	-0.002
	[0.003]	[0.005]
Mean dep. var	0.396	0.644
Observations	4,309	4,332
R-sq	0.611	0.122

Notes: This table reports results based on comparable data on village amenities from 2011 Census and 2020 Mission Antyodaya data. The dependent variable is the proportion of the available village infrastructure indicator variables, each takes the value 1 if the amenity is available in the village and 0 otherwise. These include educational institutions, sanitation, drinking water, recycling, post office, transportation, library, roads, ATM, bank, and market. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls, village controls along with boundary fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.3: Spatial RD estimates of effect on village infrastructure

	Swindex	Saubhagya	PMUY	PMMVY*	PMJAY	PMKPY	PMFBY	Organic	RGSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NewHq	-0.106**	-0.010	-0.001	-0.026*	-0.012	-0.004	-0.015	-0.004	-0.044*
	[0.046]	[0.010]	[0.012]	[0.013]	[0.013]	[0.009]	[0.011]	[0.004]	[0.024]
Mean dep. var	0.022	0.140	0.241	0.847	0.708	0.139	0.209	0.046	0.534
Observations	4,311	4,332	4,332	2,408	2,997	4,270	4,270	4,270	4,170
R-sq	0.052	0.037	0.035	0.031	0.024	0.027	0.025	0.018	0.039

Notes: The results reported in the table above are based on Mission Antyodaya village-level data for the year 2019. The dependent variable in col (1) 'Swindex' is a summary index using the standardized inverse-covariance weighted average of total beneficiaries as a share of all eligible beneficiaries under schemes in columns (2)-(9). These include (2)Saubhagya or Pradhan Mantri Sahaj Bijli Har Ghar Yojana (PMSBHY) which provides electricity connections to rural households; (3) Pradhan Mantri Ujjwala scheme (PMUY) which provides cooking fuel (LPG) cylinders; (4) Telangana equivalent of Pradhan Mantri Matru Vandana Yojana (PMMVY) which provides cash transfers to pregnant and lactating mothers; (5) Pradhan Mantri Jan Arogya Yojana (PMJAY) which is a public health insurance scheme; (6) Pradhan Mantri Kisan Pension Yojana (PMKPY) which is a pension scheme for farmers; (7) Pradhan Mantri Fasal Bima Yojana (PMFBY) which is a crop insurance scheme; (8) Organic refers to the number of farmers who adopted organic farming during 2018-19; and (9) Rashtriya Gram Swaraj Abhiyan (RGSA) which a capacity building and training scheme for rural elected representatives. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls, village controls along with boundary fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.4: Spatial RD estimates of effect on program beneficiaries

	(Y/N) (1)	log(0.01+inv) (2)	log(1+emp) (3)
NewHq	-0.078***	-0.414***	-0.309***
	[0.028]	[0.144]	[0.111]
NewHq × Distance_NewHq≤ 20	0.092***	0.506***	0.304**
	[0.027]	[0.156]	[0.112]
Mean dep. var	0.454	-2.344	1.509
Observations	2,918	2,918	2,918
R-sq	0.125	0.094	0.115

Notes: This table reports results based on data on the applications received for industrial licenses and approvals under TS-iPASS for the period 2017-18 to 2022-23. The dependent variable in column (1) "Y/N" is a binary variable that takes the value 1 if at least one application was received to set-up an establishment in the village during this period and 0 otherwise; columns (2) reports ln(0.01+inv) where inv is the extent of total proposed investment; and column (3) reports ln(1+emp) where emp is the extent of total proposed employment generated in a village under TS-iPASS during this period. Distance_NewHq≤ 20 is a dummy which takes the value 1 if the distance of the village to its new district HQ is less than equal to 20km (the 25th percentile) and 0 otherwise. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls along with boundary fixed effects. The new district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.5: Spatial RD estimate of effect on investment, employment

	2012-2016	2017-2021
	(1)	(2)
NewHq	-0.066	-0.050
	[0.051]	[0.045]
Mean dep. var	-0.748	-0.308
Observations	13,765	13,765
R-sq	0.534	0.529

Notes: The dependent variable is ln(0.01+Nightlights) trimmed at the 5th and 95th percentile. The unit of observation is at village level. The sample includes villages within a 10 km bandwidth of district boundary excluding villages around the city of Hyderabad. All regressions include two-dimensional local linear geographic controls, village controls along with boundary and year fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.6: Spatial RD estimates of effects on nightlights

	2014-2016	2017-2022
	(1)	(2)
NewHq	0.088	0.072
	[0.129]	[0.062]
Dist_NewHq	-0.002	0.0003
	[0.003]	[0.002]
NewHq $\times$ Dist_NewHq$\leq$ 30	0.096	0.116*
	[0.134]	[0.068]
Mean dep. var	8.998	8.966
Observations	52,813	117,417
R-sq	0.144	0.073

Notes: The dependent variable is ln(1+ person-days). Dist_NewHq $\leq$ 30 is a binary variable that takes the value 1 if the village's distance to its district HQ at the time is less than 30km and 0 otherwise. 30km is the median distance of a village to its district HQ in the state. The unit of observation is at GP-village level. The sample includes villages all villages. All regressions include two-dimensional global cubic geographic controls, village controls along with boundary and year fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.7: Heterogeneity of effect on NREGA employment by distance

	(1)	(2)
NewHq	0.021	-0.072*
	[0.085]	[0.039]
NewHq × hhi_dec	0.227*	
	[0.123]	
NewHq × sh_vote50		0.405***
		[0.046]
Control mean	8.966	8.966
Observations	21,906	3,851
R-sq	0.240	0.153

Notes: This table reports results based on the period 2017-2022 in column(1) and for the FY 2019-20 in column (2). The dependent variable is ln(1+person-days). 'hhi_dec' refers to a binary variable that takes the value 1 if caste fractionalization goes down in the splinter district after district reorganization and 0 otherwise. 'sh_vote50' is a binary variable that takes the value 1 if the voter turnout in the 2019 GP election was at least 50%. The unit of observation is at GP-village level. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls, village controls along with boundary and year fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.8: Heterogeneity of effect on NREGA

1.11 Appendix

1.11.1 Robustness

	Village	District
	(1)	(2)
NewHq	0.148***	0.386***
	[0.053]	[0.062]
Dep. var mean	1.296	-4.633
Observations	21,906	21,906
R-sq	0.405	0.282

Notes: The dependent variable in Column (1) is ln(.01+ person-days as a share of village population) and in Column (2) is ln(.0001+ person-days as a share of new district population). The unit of observation is at GP-village level. The sample includes villages within a 10 km bandwidth of district boundary and all regressions include two-dimensional local linear geographic controls along with boundary and year fixed effects, village controls for area, total population, proportion of population that is illiterate, proportion of cultivators. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.9: Spatial RD estimates of effect on NREGA: Normalized by Population

	log(1+Person-days)			
	(1)	(2)	(3)	(4)
NewHq	0.138**	0.189***	0.163**	0.133**
	[0.057]	[0.066]	[0.063]	[0.065]
Bandwidth	10km	20km	30km	Full
Bandwidth	Linear	Linear	Linear	Cubic
Mean dep. var	8.966	8.956	9.028	9.165
Observations	21,906	41,214	55,353	117,417
R-sq	0.235	0.198	0.162	0.072

Notes: The dependent variable is ln(1+ person-days). The unit of observation is at GP-village level. The sample in Columns (1), (2), and (3) includes villages within a 10, 20, and 30 km bandwidth of district boundary respectively. Column (4) includes the full sample of all villages in the state. Columns (1), (2), and (3) include two-dimensional local linear geographic controls whereas Column (4) adopts a global cubic polynomial approach. I also include boundary and year fixed effects, village controls for area, total population, proportion of population that is illiterate, proportion of cultivators. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.10: Effect on NREGS Work: Flexible Specification

1.11.2 Balance Test

	ΔEmployment					ΔEstablishments	
	All	Hired	Private	Manuf.	Services	Total	Private
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NewHq	-0.007	-0.050	-0.021	-0.013	-0.044	0.018	0.015
	[0.067]	[0.054]	[0.068]	[0.095]	[0.058]	[0.082]	[0.083]
Mean dep. var	0.264	0.017	0.340	0.168	0.329	0.332	0.377
Observations	2,918	2,918	2,918	2,918	2,918	2,918	2,918
R-sq	0.108	0.086	0.105	0.111	0.129	0.147	0.141

Notes: This table reports results based on Economic Census data for the years 2005 and 2013. The dependent variable in columns (1) through (5) is the percent change in total employment in all entrepreneurial units and under particular sub-heads. The dependent variable in Columns (6) and (7) is the percent change in the number of establishments, total and private respectively. The unit of observation is at village level. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls along with boundary fixed effects. The new district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.11: Spatial RD estimates of pre-treatment balance in industrial employment

1.11.3 Distance

	sh_pmmvy	sh_rgsa
	(1)	(2)
NewHq	-0.030**	-0.023
	[0.014]	[0.025]
Dist_NewHq	0.000	0.000
	[0.000]	[0.000]
NewHq × Dist_NewHq≤ 30	0.007	-0.011
	[0.014]	[0.029]
Control mean	0.880	0.593
Observations	13,338	16,163
R-sq	0.018	0.023

Notes: The results presented in this table are based on 2020 MA survey. Dist_NewHq $\leq$ 30 is a binary variable that takes the value 1 if the village's distance to its district HQ at the time is less than 30km and 0 otherwise. 30km is the median distance of a village to its district HQ in the country. The unit of observation is at GP-village level. The sample includes all villages All regressions include two-dimensional global cubic geographic controls, village controls along with boundary and year fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.12: Heterogeneity of spatial RD estimates on beneficiaries with distance

1.11.4 Corruption

One of the concerns surrounding decentralization is the risk of corruption and local capture (Bardhan and Mookherjee, 2000b; Faguet, 2014). Similarly, district reorganization gives rise to opportunities for jobs and for greater control over the public resources allocated to the newly established district. In order to test for such leakages, I look at the amount of wages disbursed to workers and different sub-categories of total expenditure incurred under NREGS.

Looking at the results for the amount of wages disbursed into workers' bank or post office accounts in Table 1.13, I find that there is a corresponding increase in the total amount disbursed to the extent of 14% in the new district villages relative to the old district villages in the post policy period. Likewise, Table 1.14 shows that the total expenditure on unskilled labor wages and vendor expenditure is higher as well for new district villages. However, there was no significant difference in the extent of material or administrative expenditure. This suggests that (1) the person-days results are less likely to be due to "ghost workers" that only exist on paper, and (2) if the labor expenditure were fudged, we should see a similar effect on material expenditure which provides greater scope for misreporting but that is not the case. Therefore, using the publicly available data on scheme implementation, I don't find support for the corruption mechanism in explaining my main results.

	ln(1+ wages_disbursal)	
	(1)	(2)
NewHq	0.045	0.131***
	[0.058]	[0.032]
Mean dep. var	2.413	2.624
Observations	8,993	21,684
R-sq	0.223	0.167

Notes: The dependent variable is ln(1+ total wages disbursed). The unit of observation is at GP-village level. he sample includes villages within a 10 km bandwidth of district boundary. All Regressions include two-dimensional local linear geographic controls and boundary and year fixed effects, village controls for area, total population, proportion of population that is illiterate, proportion of cultivators. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.13: Effect on wages disbursed

	Log(Expenditure)			
	Material	Admin.	Unskilled	Vendors
	(1)	(2)	(3)	(4)
NewHq	0.026	-0.005	0.146***	0.069*
	[0.023]	[0.008]	[0.035]	[0.040]
Mean dep. var	1.318	0.269	2.606	1.966
Observations	21,778	21,778	21,778	20,573
R-sq	0.549	0.520	0.189	0.136

Notes: The dependent variable in Column (1), (2), (3) is ln(1+total expenditure on particular category), and in Column (4) is ln(0.01+ total expenditure on vendors). The unit of observation is at GP-village level. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls, village controls along with boundary and year fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.14: Effect on NREGS expenditure

1.11.5 Elite Capture

Elite capture is an important concern surrounding decentralization. In this scenario, bringing administration closer to local actors could lead to program benefits being disproportionately enjoyed by the more well-off households. To test if this is the case, I look at the NREGS beneficiaries, disaggregated by their caste. I find that in absolute terms, the increase in person-days generated under the scheme is shared by households belonging to disadvantaged caste as well as women. Likewise, I do not find a worsening in the share of these caste in the total person-days under the scheme. This is not surprising given that NREGS work is often considered a last-resort activity by rural households. However, the same cannot be said for women who witness a decrease in their share in the program benefits. There is a possibility that revival of the scheme under new district administration led to greater competition for work between the genders that crowded out women as documented by (Afridi, 2022). These results are presented in Table 1.15

	Log(1+Person-days)			Share in Total Person-days		
	SC	ST	Female	SC	ST	Female
	(1)	(2)	(3)	(4)	(5)	(6)
NewHq	0.191**	0.368*	0.114*	0.087	0.407	-1.772**
	[0.086]	[0.205]	[0.059]	[0.977]	[1.565]	[0.668]
Mean dep var	6.594	4.332	8.484	20.987	20.110	63.038
Observations	21,778	21,778	21,778	21,586	21,586	21,586
R-sq	0.125	0.369	0.236	0.171	0.359	0.316

Notes: The dependent variable in Column (1), (2), (3) is ln(1+Person-days for a particular group), and in Columns (4), (5), (6) is person-days generated for a particular group as a share of the total person-days. The unit of observation is at GP-village level. The sample includes villages within a 10 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls, village controls along with boundary and year fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.15: Effect on NREGS employment by group

1.11.6 Size

District Reorganization results in the creation of newer, smaller districts. Therefore, if this was the underlying mechanism, the benefits from the reduction in district size in terms of lower bureaucratic burden and administrative convenience should also accrue to the old district. In order to test whether this was the case, I estimate my baseline equation using NREGS data between the villages on the border of Telangana and its neighboring state of Andhra Pradesh (AP). Unlike my main results, I looked at villages within a smaller bandwidth and also controlled for distance to the headquarter. I do this to control for the effect of pre-existing difference in outcomes due to different district headquarter between the two sets of villages. These results are presented in Table 1.16. Looking at the year immediately before and after the scheme [27], I find no significant difference between the old Telangana district villages and AP villages, before or after the district reorganization. However, there is still a positive effect on new district villages relative to AP villages.

	Log(1+Person-days)	
	2015	2017
	(1)	(2)
Tel=1	-0.288	-0.057
	[0.359]	[0.162]
Tel=1 × NewHq	0.347	0.340*
	[0.558]	[0.190]
Mean dep. var	9.053	9.223
Observations	550	550
R-sq	0.199	0.089

Notes: The dependent variable in Column is ln(1 + Person-days). The unit of observation is at GP-village level. Tel is a dummy variable which takes the value 1 if the village belongs to the state of Telangana and 0 if the village belongs to the neighboring state of Andhra Pradesh. The sample includes villages within a 5 km bandwidth of district boundary. All regressions include two-dimensional local linear geographic controls, village controls along with village distance to old district HQ. I also include boundary and year fixed effects. The splinter district-level clustered standard errors are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.16: Effect on NREGS: AP vs TEL

[27] Since the policy change occurred during the middle of 2016, therefore I look at the outcomes during 2015 instead.

1.11.7 State Politicians

Although district reorganization left the political constituency boundaries unchanged, it is possible that the creation of new party posts and the opportunity for rent-seeking by colluding with the new district administration led to the entry of new political participants.

To test this if this channel drives my results, I obtained constituency-candidate-level data for the State Assembly Elections for the years 2014 and 2018 from Triveni Centre for Political Data (TCPD) and Association for Democratic Reforms and SHRUG. This includes information on candidates' age, gender, caste, education, assets, liabilities, and votes received. I adopted a difference-in-differences design to compare the extent of electoral competition and the characteristics of political candidates in the political constituencies in the new and old districts after the policy change (results reported in Tables 1.17 and Table 1.18). There is no significant difference in the number of candidates, general or disadvantaged caste, or voter turnout. Looking at the individual candidate characteristics, the only significant difference is in the higher likelihood of the wining candidate having any liabilities by 14.6pp. Hence, I do not find support for the political channel using state assembly elections data.

	Candidates (No.)	Turnout (%)	Candidate SC/ST
	(1)	(2)	(3)
New District × Post	0.332	1.386	-0.008
	[0.760]	[2.430]	[0.021]
Control mean	13.618	68.168	0.165
Observations	476	357	3,935
R-sq	0.436	0.803	0.646

Notes: This table presents the DID estimates on the effect of district reorganization on political competition using data on state assembly elections for the years 2014 and 2018. New District dummy equals 1 if largest segment of the constituency lies in a newly created district. All regressions include constituency-level controls-number of electors, area. Fixed effects are at the parent districts level. The splinter district-level clustered standard errors are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.17: DID estimates: Political competition

	Age	Female	10th grade+	Graduate Graduate	Log (Assets)	Liabilities (0/1)	Criminal Cases	Margin (%)	Incumbent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Winning Candidate								
New District × Post	-0.644	0.037	0.030	-0.054	-0.025	0.146*	1.411	1.033	-0.029
	[1.171]	[0.037]	[0.027]	[0.063]	[0.396]	[0.076]	[1.324]	[2.025]	[0.078]
Control mean	43.410	0.076	0.852	0.461	13.957	0.392	0.347	3.145	0.037
Observations	468	476	476	427	371	372	442	476	476
R-sq	0.108	0.060	0.072	0.154	0.318	0.125	0.057	0.150	0.080
	Panel B: All Candidates								
New District × Post	-0.463	-0.012	0.016	0.036	0.143	0.003	0.063	0.103	-0.007
	[0.506]	[0.016]	[0.017]	[0.027]	[0.125]	[0.030]	[0.173]	[0.128]	[0.006]
Control mean	43.410	0.076	0.852	0.461	13.957	0.392	0.347	3.145	0.037
Observations	7,111	7,275	7,275	6,557	5,286	5,509	6,845	7,275	7,275
R-sq	0.155	0.013	0.036	0.044	0.365	0.124	0.074	0.595	0.166

Notes: This table presents the DID estimates on the effect of district reorganization on politician characteristics using data on state assembly elections for the years 2014 and 2018. New District dummy equals 1 if largest segment of the constituency lies in a newly created district. All regressions include constituency-level controls-number of electors, area. Fixed effects are at the parent districts level, Panel B also includes candidate position fixed effects. The splinter district-level clustered standard errors are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 1.18: DID estimates: Political candidates quality

1.11.8 District Collectors

One channel that might influence the effect of district reorganization on local outcomes is the reallocation of manpower across new districts. Given the fixed cadre strength of civil servants, creation of new districts led to a shortage of IAS officers to fill the important post of district collectors in the new districts. This shortage was addressed by promotion of non-cadre officers and more junior IAS officers to the post of district collectors on ad-hoc basis. On one hand, younger officers bring fresh ideas and zeal to the post, On the other hand, their inexperience might adversely affect their performance.

Another measure to address this issue was to put the new districts under full additional charge (FAC) of the old district's collector. Although the old district's collector might have experience managing the workload of the previously unified jurisdiction, the establishment of separate offices for the new districts could lead to efficiency losses.

To explore the role of this channel, I extract information on district collector postings by web scraping digitally archived snapshots of Telangana State Government's website. Since these snapshots are available sporadically during a year, to create a complete district collector-level database, I fill in the gaps by using information contained in the transfers and postings orders from the General Administration Department, published on Telangana's Government Order Issue Register website. For district collectors who are IAS officers, I further merge in detail on officer characteristics such as age, gender, allotment year, education etc. obtained from TCPD. The t-tests results to determine if there is a significant difference between the district collectors of the new and old districts are presented in Table 1.19. These lend support for the anecdotal evidence on the deployment of district collectors of old districts as FACs of new districts. However, I do not any significant difference in other attributes of the district collectors posted in the new versus the old districts. Nevertheless, in order to conclusively establish the role of divided administrative attention on program outcomes would require more detailed information on time usage of the bureaucrats.

	Old HQ (1)	New HQ (2)	Mean Difference (3)	(s.e.) (4)	N (5)
All Officers					
FAC	0.03	0.06	-0.04*	(0.02)	946
IAS	0.61	0.58	0.03	(0.04)	946
Vacancy	0.01	0.02	-0.01	(0.01)	946
IAS Officers					
Graduate	0.31	0.24	0.07*	(0.04)	584
Home	0.37	0.43	-0.06	(0.04)	584
Female	0.28	0.29	-0.01	(0.04)	584
Age (years)	38.61	39.12	-0.51	(0.78)	584
Years in Service	7.03	6.52	0.51	(0.37)	584
Direct Recruitment	0.69	0.63	0.06	(0.04)	584

Note: Difference is defined as Old HQ - New HQ.
Observations are at the (district, time, post) level from 2016-present.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.19: Bureaucrat Characteristics T-test

2

Impact of Cash Transfers to Farmers: Agricultural Productivity and the Labor Market

2.1 Introduction

Low agricultural productivity and misallocation of labor across sectors in developing countries is considered a major impediment to bridging the income gap with the developed countries (Gollin et al., 2014; OECD, 2014; UNCTAD, 2015). In India, farming is in a state of crisis with protests over agricultural policies and a farmer suicide "epidemic" spurred on by falling farm incomes (BBC, 2015; NYT, 2020). In response, governments generally offer a wide range of support to farmers from input subsidies, technical assistance, to price support. For instance, as per a 2019 Finance Commission report, farm subsidies formed 2-2.25% of India's GDP and 21% of aggregate farm income in 2017-2018. At the same time, agricultural subsidies can also end up being distortionary (Theriault and Smale, 2021), and regressive (Donovan, 2004).

Recently, there has been a renewed interest in the role of cash transfers (CTs) as a safety net as witnessed by the popularity of GiveDirectly (Haushofer and Shapiro, 2016). In theory, farmers can finance input purchases from farm savings, from non-farm income sources, or from borrowing. In reality, small and marginal farmers in developing countries are unable to save and lack access to credit markets that limit their ability to make productive investments thereby reducing their productivity. Cash transfers could address this by relaxing those binding credit constraints. Further, the insurance effect of assured future cash receipts could lessen household's precautionary savings which may then be diverted towards making more risky investments.

While the impact of cash transfers on social outcomes like health and education has been extensively studies (Manley et al., 2013; Baird et al., 2014), evidence of the impact on productive investments and labor market related outcomes is limited (de Mel et al., 2008, 2012; Blattman et al., 2016; Banerjee et al., 2017; Baird et al., 2018; Handa et al., 2018). Research on the general equilibrium effects of CTs is even rarer (Bandiera et al., 2017). To some extent, this can be explained by the fact that CTs are generally targeted to poor and vulnerable groups as a social protection policy tool. This often includes orphans or vulnerable children, women, youth, elderly, refugees, and the ultra-poor. Additionally, the effect on economic outcomes may take longer to materialize than the duration of most evaluations.

In this paper, I will look at impact of cash transfers on the agricultural decisions of farmers in the context of India. In May 2018, the government of Telangana state (GoTS) launched Rythu Bandhu scheme to provide lump-sum cash transfers to farmers [1]. The total scheme outlay formed a 3.5% of the state's annual budget. These transfers were unconditional but labelled as 'farmer's investment support scheme'.

[1] A detailed description of the scheme design and its implementation is available in Muralidharan et al. (2020)

Payments were made at the beginning of the cropping season to give farmers enough time to make decisions regarding investment in inputs such as seeds, fertilizers, and hired labor; productive assets, crop choice etc. The transfers were made on per hectare basis such that larger farmers received greater payments. This attribute of the policy will allow me to look at the heterogeneous effects of scheme with respect to farm size. Further, these transfers were only made to landowning farmers, so I would be able to look the spillover effects of the scheme, if any, on tenant farmers as well as non-agricultural households.

To evaluate the impact of the scheme on farm outcomes as well as the household's labor resource allocation, I use household level data from two rounds of a repeated-cross sectional government survey of Indian farmers, conducted before (2012-13) and after (2018-19) the scheme implementation. Since the scheme was launched in all the districts of the state at the same time, I employ a difference-in-difference (DID) strategy to compare mean outcomes in Telangana to those in the neighboring districts of bordering states, for both beneficiaries and non-beneficiaries separately.

My first set of results look at the effect of the scheme on farm outcomes of large farmers. My DID estimates indicate that treated farmers' crop yield increased by 10.7pp and the total value of the output produced per hectare went up by 23.1pp. The latter was in part due to a rise in the rate at which farmers were able to sell their produce by 11.5pp. These results can be explained by two channels. Firstly, input expenditure per hectare of larger farmers goes up by 34.8pp in Telangana. Secondly, even though the probability of making a productive investment remains unchanged, the amount of expenditure on the net purchase of farm assets per hectare increased for large agricultural households by almost double. Looking at treatment effect for small farmers, I find no significant impact on the crop yield or the total value of output per hectare although they too experience higher sale rate by 8.3pp. This could suggest improved bargaining power or output quality. Likewise, the results for input expenditure show no significant difference between the treated and control small farmers, however, the treated small farmers significantly increase their investment in the net purchase of agricultural tools by 75pp.

Next, I examine the effect of the scheme on labor market allocation of treated households in Telangana. On one hand, adult members of large landholding households become more likely to be self-employed in agriculture, particularly as helpers, and less likely to be engaged in education as their principal activity. On the other hand, small treated farming household members become more likely to be engaged in casual agricultural labor as their principal economic activity and less likely to be working as an own-account worker on their farm. Instead, they were more likely to be self-employed in agriculture as a subsidiary economic activity. This suggest a re-allocation of labor between small and large treated households in Telangana.

For these results to be valid, the outcome variable must satisfy the parallel trends assumption under DID analysis. To this end, I conduct a falsification test using two rounds of pre-policy period survey data and find no significant difference between the landowning households, small or large, between Telangana and its neighboring districts. Finally, I explore if there were any spillover effects of the scheme on untreated households within Telangana. However, I find no evidence of any significant impact on the tenant farmers or the non-agricultural households.

This paper complements studies that have looked at the effects of cash transfers on economic outcomes. Studies that looked at the effect of a cash grant to entrepreneurs find an increase in micro enterprise ownership, business assets, earnings, and labor supplied although the size of impact varied with the entrepreneur's characteristics including gender and ability (McKenzie and Woodruff, 2008; de Mel et al., 2008, 2012, 2014; Fafchamps et al., 2014; Blumenstock et al., 2016; Blattman et al., 2016; McKenzie, 2017). If an agricultural household or entrepreneur is credit constrained, they may not be able to exploit productive investments opportunities. In such a case, transfers can improve economic outcomes by infusion of capital. Even, when cash transfers are not conditional on work, households might divert some funds towards investments. Evidence from the evaluation of several such cash transfer schemes is mixed. Some show an increase in input expenditure, livestock holdings, and non-farm activities (Covarrubias et al., 2012; Gertler et al., 2012) while others don't observe any change (Maluccio, 2010). The size of impact depends on the size, frequency, timing (Duflo et al., 2011), conditionality, and predictability of the transfers along with the characteristics of targeted group. Given that the RBS transfers were large (compared to average farm income), provided at the beginning of the cropping season, and labelled (Benhassine et al., 2015) as 'investment support' potentially contributed to the results I observe in this paper.

My paper also complements research that looks at the effect of liquidity on rural labor markets. Relaxing credit constraints can improve the scope for greater investment and higher profitability from farming leading to greater labor participation in the agricultural sector (Ervin et al., 2017; Fink et al., 2020). Cash transfers can also affect individual's labor market outcome by changing choice of sector and location. Increase in consumption resulting from the receipt of cash transfers can lead to increased demand for local non-tradable goods creating more jobs in the non-agricultural sector (Emerick, 2018). Another channel works by removing the barrier of search cost and/or entry cost thereby facilitating migration (Bryan et al., 2014; Abebe et al., 2021; Akram et al., 2017) and promoting entrepreneurship (Bobba, 2013). On the other hand, income effect might result in reduced labor supply although there isn't strong evidence to support that except in the case of elderly who might retire early when they receive social pensions. In my paper, I find support for the profitability channel.

I also contribute to more recent works that look at the general equilibrium and spillover effects of cash transfers. In addition to affecting individual outcomes, large cash transfers can also provide stimulus to the local economy. The price effects of transfers work through increased aggregate demand from beneficiaries increasing their consumption and assets as documented by Cunha et al. (2019); Filmer et al. (2023); Egger et al. (2022). This rise in prices could adversely affect households' purchasing power and offset some of the gains from cash transfers as noted by Filmer et al. (2023) who find that the increase in food prices led to increased stunting among the children from non-beneficiary households. The increase in consumption of beneficiaries could impact non-beneficiaries though other channels as well. For instance, Angelucci and Giorgi (2009) find that non-beneficiary households increase their consumption using gifts and loans from beneficiaries while Egger et al. (2022) find that non-recipients' income gain is driven largely by increases in their wage labor earnings. However, in my paper, I find no spillover effects on non-beneficiary households despite the large size of the scheme.

The remainder of this paper is organized as follows. Section II describes the setting, design, and implementation of the policy. Section III provide the conceptual framework; Section IV details the data; Section V outlines the identification strategy and estimating equations. Section VI presents the main results and Section VII concludes.

2.2 Background

2.2.1 Setting

The Indian state of Telangana is a newly formed state, carved out of the united state of Andhra Pradesh in 2014. Most of its population is rural and agricultural: as per the 2011 Population Census of India, 61% of state's population lived in rural areas and 55% of them worked in the agriculture sector.

The agricultural sector, which contributed 16.4% to the state's GDP in 2019-2020, constitutes of many small and marginal farmers. Of all landholding farmers, 88% have less than 2 hectares. Of these, 43% of the households hold no land, among which 20% are tenant farmers who lease their land from the actual landowners (GoT, 2017). Further, there are wide disparities across different caste and gender groups in their share of the total agriculture operational area in the state. For instance, the share in the total operational holdings is greater among Scheduled Tribes (STs) at 12% compared to Scheduled Castes (SCs) at 13% relative to their respective share in the population[2].

There are 21 principal crops grown over an average area of 11,818.51 ('000) hectares[3] across the two main cropping periods, namely Kharif and Rabi, during the

[2]These numbers have been calculated using 2011 Agricultural Census data by aggregating the respective Census figures over the districts that approximately constitute present day Telangana.

[3]As per the 2017-18 to 2021-22 Normal Estimates released by the Directorate of Economics &

period between 2017-18 to 2021-22. Th major crops grown are Rice, Maize, Pulses, Groundnut, Cotton, Chillies, and Sugarcane. A majority of the area, around 87%[3] was sown during the Kharif season. Another characteristic of agriculture in the state and in the country, more generally, is the heavy reliance on the southwest monsoon rainfall during the Kharif season since the net irrigated area only accounts for a fraction[4] of the net sown area.

Given the significant role of the agriculture sector in rural development and the electoral strength of the farming community, the Central and the state Governments have introduced a plethora of schemes which offer wide-ranging support to the farmers from input subsidies, price support, crop insurance to debt waivers which have had mixed results in achieving their goal of improving efficiency and incomes, and reducing farm distress (Gupta et al., 2021; Kanz, 2016; Lybbert et al., 2024). Unlike the existing support structure, RBS offers unconditional assistance to targeted group of farmers that is proportionate to the size of their landholding. Given these distinct aspect of the scheme, its impact on farm outcomes calls for further exploration. I discuss specific features of the scheme and its implementation in further detail in the next section.

2.2.2 About the Scheme

To channel investment into farming inputs, the Government of Telangana introduced the Rythu Bandhu scheme (Rythu or RBS henceforth[5]) in May 2018.

Statistics, DAC&FW

[4] 49% to be precise, as per Land Use Statistics released by the Directorate of Economics & Statistics, DAC&FW

[5] Also known as Farmer's Investment Support Scheme

The scheme initially offered Rs. 4,000 ($55) to landowning farmers per acre per agricultural season. Thus, the total annual per acre payments amount to Rs. 8,000 ($110) which is released in two equal installments. This amount was later increased to Rs.5000 per acre per season. Therefore, the eligibility and the size of scheme benefits depends on the extent of agricultural land owned by the farmer. For instance, a farmer who owned 0.5 acre of land only received half of the benefits compared to the farmer who owned 1 acre of land. As per Muralidharan et al. (2020) survey data, the average transfer amount received was Rs. 8,817, while the median amount was Rs. 5,280 .

Since the targeting and payment amount are based on landownership as reflected in land titles records in the State government's land records, to rectify previous errors and ensure smooth scheme implementation, land records were digitized and updated prior to the scheme roll-out. Payments are directly transferred into the beneficiary bank accounts[6] prior to the start of each season to facilitate its use in making agricultural investments although there is no restriction on its utilization. The farmers may use these funds to the purchase of farm inputs and assets, to pay off their debt, or to supplement consumption[7].

Under RBS, the group of landless farmers which is comprised of tenant farmers, who cultivate leased-in land, and agricultural laborers, who till the landowner's land, are excluded from receiving the benefits under the scheme[8]. Further, there is

[6]Initially, due limited information about beneficiary bank accounts, given the short time frame of the scheme launch, the benefits were distributed to farmers by way of bank checks.

[7]In fact, anecdotal evidence lends support to this speculation as it is found that small and marginal farmers found the sum of money received under the scheme to be inadequate to make productive investments or reduce their indebtedness (The Hindu, 2019)

[8]In terms of income and debt, landless farmers are similar to small and marginal farmers (Ghosh and Vats, 2022).

also no cap on the number of eligible acres although the Government of Telangana appeals to larger and wealthier farmers to voluntarily "Give it up" rather than accept support under the scheme. This along with the proportional payment structure of the scheme design results in inequitable distribution of benefits across different land-holding and landowning sub-groups. This attribute of the scheme warrants closer examination and would thus guide the empirical design employed in this study and is discussed in further detail in Section IV.

The RBS is a large-scale cash transfer program. In the first year of its implementation (2018-2019), the total outlay was approximately Rs. 12,000 crores ($1.8 billion). In comparison to that year's total expenditure, the program constituted around 9% of Telangana's state spending (GoT, 2018). In comparison to the average Telangana farming household which holds 1 hectare, the scheme provides about one month's income per year (NYT, 2021). The cash transfers of $110 annually are comparable to most government transfers like those made under Malawi's Social Cash Transfer scheme ($4 pm to $13 per month) or Zambia's Child Grant Program of $12 per month.

Following the success of RBS in Telangana, the Central Government and a few other State Governments launched similar cash transfer schemes targeted towards farmers. Even in the case of RBS, the budgetary allocation for the scheme has gone up from Rs 120 billion to Rs 150 billion from 2018-19 to the year 2023-24. Given the rising popularity and scale of schemes that provide unconditional cash transfers to farmers, it is prudent to examine if the scheme had the intended effect and investigate any unintended consequences.

2.3 Conceptual Framework

In this section, I first present a general discussion of the decision making of agricultural households and how cash transfers can potentially affect their behavior, and then I interpret it in the context of RBS design and implementation in India as a special case. According to the agricultural household model (Singh et al. (1986)), in the absence of market failures, the production and consumption decisions are "separable" and in such a case, transfers have no effect on the household production decisions and only affect consumption by relaxing the budget constraint. However, most developing economies suffer from multiple market failures and as a result, consumption and production decisions are interdependent and transfers can also have productive impacts.

First, given the seasonal nature of agricultural production and the lumpy nature of investment, agricultural households may be unable to incur optimal level of input expenditure during planting season when the disposable income is low. Further, small farmers may lack the collateral to obtain credit to finance investment. Additionally, due to asymmetric information and issues of adverse selection, banks may be reluctant to lend to farmers who are in most need of a loan. Therefore, when agricultural households face liquidity and credit constraints, cash transfers promote investment by improving relaxing these constraints (Rosenzweig and Wolpin (1989); Gertler et al. (2012); Handa et al. (2018)).

Second, lack of trust, financial illiteracy, and inadequate information along with price sensitivity results in incomplete insurance market in developing countries. In presence of insurance market constraint, risk-averse farmers, uncertain about their ability to recover from shocks, opt for a low-risk, low-return portfolio. Cash transfers by promising a steady stream of future income reduce the downside risk and expand production choice by allowing farmers to invest in improved seeds, fertilizers, and cash crops (Serra et al. (2006); Akresh et al. (2016); Varshney et al. (2021);Ghosh and Vats (2022)).

Third, in agriculture, worker effort is costly to monitor and output is uncertain which makes family labor and hired-in labor imperfect substitutes for each other. There are also high transaction costs-search and fixed costs. By raising the non-labor income, cash transfers can affect household production decisions by a reallocation of household labor between on-farm and paid labor as well as by a change in the demand for hired-in labor (Todd et al. (2010); Covarrubias et al. (2012); Prifti et al. (2019)). Since households sell agricultural wage labor is a risk coping strategy, cash transfers would have a negative effect on this activity.

While the impact on input and investment is predicted to be positive, the impact on other farm related outcome does not necessarily have to be positive. Increase in assets and inputs might not translate in improved output if farmers do not employ them efficiently. Farmers may also use cash transfers to repay debt from local moneylenders or debts levels could increase owing to improved ability to repay loans. Likewise, households could either reduce their precautionary savings or save more in anticipation of future increased income. Similarly, the effect on family farm-labor and non-agricultural labor would depend on the relative profitability of these activities. Since income elasticity of income in this context is low, impact on leisure is likely to be muted except potentially in the case for women and children. The net effect of cash transfers is influenced by the design features and the implementation of the policy such as size, frequency, conditionality and so on.

According to the framework outlined above, the impact of RBS on farm outcomes cannot be determined a priori. Below, I discuss some of the features of the scheme that could potentially affect the direction of the change.

First, RBS offers farmers Rs. 8000 per acre per year which given the average holding size of landowning households of 2.14 acres[9] amounts to Rs. 17,120 per year. With the average annual input expenditure per agricultural household during the agricultural year July, 2012 to June, 2013 was Rs. 72,607[10], the transfer amounts to roughly 23.5 percent of the annual input expenditure which is a decent sum. Therefore, depending on the landholding size, it is likely to be applied towards productive investment instead of consumption smoothening (Bastagli et al. (2019)). The same principle applies to the extent and nature of household labor reallocation.

Second, the transfers are made at the beginning of each agricultural season. This timing was to ensure that farmers had enough time to employ the funds towards the purchase of agricultural inputs and assets such as bullocks, manure, irrigation, and hiring labor in advance of the sowing season (April-May). In its first year of implementation, however, fund distribution delayed until the first week of May (Muralidharan et al. (2021)). Further, since the transfers are made in lump-sum twice a year instead of monthly payments, it is more likely to be applied towards the purchase of more lumpy investments (Haushofer and Shapiro (2016)).

Third, the scheme is specifically targeted towards landowning agricultural

[9] As per 2018-2019 Situation Assessment Survey of Agricultural Households data.

[10] Based on 2012-2013 Situation Assessment Survey of Agricultural Households data, the average monthly input expenditure for crop production in Telangana was Rs. 4,267. As per Central Statistics Office (CSO), the All-India Consumer Price Index for rural areas for July, 2018 was 141.8 with 2012=100.

households, excluding landless and tenant households. The rationale behind this policy decision was primarily influenced by the logistical ease of identifying beneficiaries through official land records, rather than being based on actual need. Nonetheless, tenant households could benefit from the policy if their landlords pass on the cash benefit in the form of lower rents. Additionally, if beneficiary households' increase their demand for hired-in labor, this could drive up the agricultural wages and create employment opportunities for ineligible households.

Finally, although RBS does not have explicit conditions for its application, the fact that the scheme is called as Farmer's Investment Support Scheme can influence how the transfers are used by the beneficiary households. This form "labelling" or "soft conditionality" is shown to have the intended effect similar to a "hard" conditional cash transfer scheme (**?**).

In sum, the productive impact of RBS depends on the outcomes under consideration, how they interact with the scheme design and the way the scheme was implemented in the context of Telangana. In the following sections, I discuss the data and empirical strategy I follow to estimate the causal effect of RBS on agricultural households.

2.4 Data

My main data source in this paper is the Situation Assessment Survey (SAS) of Agricultural Households conducted by the National Sample Survey Office (NSSO). I rely on the three rounds of the survey conducted so far: 59th Round (January - December 2003), 70th Round (January - December 2013), and the 77th Round

(January-December 2018). The SAS is a nationally representative, repeated-cross sectional survey of Indian farmers in rural areas of the country. Each round gathers information pertaining to the two halves of the preceding agriculture year (July-June)[11], loosely corresponding to the two main cropping seasons known as Kharif and Rabi. Each sample household is visited[12] twice; first during January to July and then again during August – December to collect data for the period between July to December of last year and January to June of current year respectively.

The data includes a comprehensive record of crop-wise land under cultivation, irrigation status, input expenditure, and output-produced and sold. In addition, it incorporates information regarding the receipts and expenses of households' farm and non-farm businesses, consumption expenditure, sale and purchase of productive assets, access to technical advice, insurance coverage, and indebtedness. Important details of household characteristics including land ownership and demographic information of its members including the sector and type of each member's principal and subsidiary economic activity are also available.

The timing of the latest round of the survey is ideal for analyzing the short-term impact of RBS since it was conducted 6 months after the scheme was launched. Information on possession of land, owned and leased, allows me to identify the intended beneficiary households since the scheme was targeted only to registered landowning farmers. Thus, my overall estimation sample includes all agricultural households in the state of Telangana and its neighboring districts from the bordering states of Andhra Pradesh, Karnataka, and Maharashtra. I rely on the data from the

[11] Similar to a fiscal year, an agricultural year y spans from July of calendar year y and extends to June of calendar year $y + 1$.

[12] Hence, in the remainder of the paper, I use the terms "visit" and "season" interchangeably when referring to the SAS data

two latest rounds, 70th and 77th, conducted right before and after the scheme to estimate the treatment and spillover effects. I utilize the 59th and 70th rounds of data collected during the pre-policy period to conduct a falsification test.

I also use additional datasets in this paper. For testing the parallel trends assumption, I use annual, district-level estimates of area, production, and yield of various crops across states for the years 2010-2017. This data is published by the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare.[13] Additionally, I also utilize the first two rounds of the Period Labor Force Survey (PLFS) pertaining to the period July, 2017 - June, 2018 and July, 2018 - June, 2019. PLFS is a national, repeated cross-section, annual survey conducted households in rural areas[14] on a quarterly basis. As a result, independent estimates can be generated for each quarter. I use this data to look at the effect, if any, of RBS on non-agricultural households in rural areas since these are not covered under the SAS.[15]

Finally, given the crucial role of weather on agricultural productivity, I also make use of data on rainfall (in meters) and temperature (in Celsius) for my sample. I utilize ERA5-Land reanalysis dataset, a high-resolution (0.1 by 0.1 degree) gridded satellite data compiled by the Climate Research Unit. For both temperature and rainfall , I combined monthly estimate for my sample districts using QGIS software

[13]These estimates are submitted by the State Government which collects it from one of their departments namely Department of Agriculture or Directorate of Economics & Statistics which is designated as the State Agricultural Statistics Authority (SASA).

[14]The survey in rural areas is conducted by visiting only 25% first stage units of the annual allocation that are being covered during the survey. It uses a rotational panel design for urban area but I will skip further details regarding it since that is not the main focus of this paper.

[15]The 77th SAS does survey non-agricultural households separately as independent strata in the two stage stratified sampling design but the same is not true for previous SAS rounds which only considered agricultural households.

and official district shapefiles to calculate total southwest monsoon[16] rainfall, and the maximum temperature for each cropping season.

2.5 Identification Strategy

I employ a difference-in-difference (DID) strategy to compare mean outcomes in Telangana to those in the neighboring districts of other states before and after the intervention. I report intent-to-treat estimates in this paper since I cannot explicitly identify RBS beneficiaries in my data. This is not too concerning as the scheme "implementation was imperfect but still fairly successful [...] corruption was not a major issue" (Muralidharan et al., 2020).

The districts used as a comparison group for Telangana lie in the neighboring states of Andhra Pradesh, Karnataka, and Maharashtra[17]. These districts are a reasonable control group as they roughly belong to the same agro-ecological zone[18] and similar administrative capacity as the districts of Telangana. The use of Andhra Pradesh is especially credible since the two states were part of the unified state of Andhra Pradesh until 2014. Thus, the administrative infrastructure and the quality of governance of the two states are comparable. Table 2.1 presents summary statistics of the estimation sample.

I classify treated farmers as "small" if the total land possession is less than

[16]Southwest monsoon brings rain to the Indian subcontinent from June to September which coincides with the Kharif season but also provides moisture for the soil for the upcoming Rabi season.

[17]These districts are Guntur, Krishna, Kurnool, Prakasam, West Godavari, and East Godavari from Andhra Pradesh, Bidar, Gulbarga, Raichur, and Yadgir from Karnataka, and Chandrapur, Garhchiroli, Nanded, and Yavatmal from Maharashtra

[18]As per agro-ecological regions defined by the National Bureau of Soil Survey & Land Use Planning

1 hectare and "large" otherwise. This is not to be confused with the classification of land holding under the Indian Agriculture Census.[19]. I estimate the treatment effect for the two groups separately. This is my preferred specification as opposed to (1) using the entire sample of farmers, and (2) a triple difference strategy with either the small farmers or the landless farmers as another control group within Telangana. I do this for two reasons: firstly, small and marginal farmers are comparable to landless farmers (Ghosh and Vats, 2022) and face different incentives and opportunities to invest on their land compared to the larger farmers, and secondly, to allow for the effect of variables such as household size (or labor) on agricultural yield to vary with farm size.

I obtain the DID estimate of the impact of RBS on households by running the following regression equation:

$$Y_{i,d,s,t} = \beta_0 + \beta_1 Rythu_{i,d,s,t} + \gamma X_{i,d,s,t} + \delta Z_{d,t} + \alpha_d + \tau_t + \epsilon_{i,d,s,t} \tag{2.1}$$

where $Y_{i,d,s,t}$ is outcome variable of interest for household i in district d in state s in year t. $X_{i,d,s,t}$ are household (or individual) level controls and $Z_{d,t}$ are district level controls for weather. α_d and τ_t are district, (visit, year) fixed effects respectively.[20] The district fixed effects account for time-unvarying differences across districts such as soil type. Standard errors are clustered at treatment i.e., the state level. But, since there are only a few clusters, wild cluster bootstrap p-values is

[19] https://pib.gov.in/Pressreleaseshare.aspx?PRID=1562687

[20] For crop level analysis, I also include crop-visit fixed effects here visit stands for season and capture season-varying yield differences across crops.

estimated based on 999 replications using Webb weights to establish significance. Further, I estimate the above equation using sample weights. The main coefficient of interest is β_1 on $Rythu_{i,d,s,t}$ which is a dummy variable that takes the value 1 for landowning agricultural households in Telangana during 2018-19 and 0 otherwise. I estimate the above equation separately for small and larger farmers.

I test for the key identification assumption of parallel trends in the years prior to the program (2010–2011 to 20017–2018) by estimating the equation below using aggregate annual yield data for major crops at the district-level.

$$Y_{c,d,s,t} = \beta_0 + \sum_{k=2010,k\neq 2017}^{2018} \beta_k Tel_s * \mathbb{1}(Y = k) + \delta Z_{d,t} + \alpha_d + \tau_t + \gamma_{c,t} + \epsilon_{c,d,s,t} \quad (2.2)$$

where $Y_{c,d,s,t}$ is crop yield variable for crop c in district d in state s in year t. $Z_{d,t}$ are district level controls for weather. α_d, τ_t, and $\gamma_{c,t}$ are district, year, and crop-season fixed effects respectively. The year effects capture common shocks to productivity that would not be accounted for by weather variables, district fixed effects account for time-unvarying differences across districts such as soil type, and crop-season fixed effects capture season-varying yield differences across crops. Tel_s is a dummy which takes the value 1 for the treated districts of Telangana and 0 otherwise. $\mathbb{1}(Y = k)$ is an indicator function for the year k. Standard errors are clustered at treatment i.e., the state level. But, since there are only a few clusters, wild cluster bootstrap p-values is estimated based on 999 replications using Webb weights to establish significance.

The set of coefficients β_k capture the differential effect of being in Telangana on the crop yield relative to the period immediately prior to the treatment i., 2017. Based on the coefficients reported in Table 2 and the event study graph shown in Figures 1, I reject the null hypothesis of parallel trends.

2.6 Results

2.6.1 Effect on farm outcomes

Table 2.3 reports the estimates of the impact of RBS cash transfers on large farmers' agricultural productivity based on crop-by-visit level analysis for the 21 major crops cultivated in Telangana[21]. Column (1) uses crop yield and Column (3) uses the total value of output including the valuation of the output produced along with proceeds from the pre-harvest sale and the sale of by-products as the dependent variable. The estimates for the impact of the scheme on the price received by the farmer is presented in column (2). The coefficient for the Rythu is positive and significant in all columns (1) to (3). These results suggest that large landowning farmers in Telangana increased their output quantity per hectare (yield) and output value per hectare by 10.7pp and 23.1pp respectively. Further, the rate at which the farmers sold their output which acts a proxy for the local market price increased by 11.5pp [22].

[21] These include Rice, Maize, Jowar, pulses, Sugarcane, Chillies, Turmeric, Onion, oil seeds, and Cotton

[22] This could be a result of better quality of the output produced or the effect of better bargaining power while selling their output owing to minimum income support offered by the cash transfers. However, in the absence of additional data, it is not possible to pin-point the exact underlying cause.

Table 2.4 presents the DID estimates for the change in net expenditure on the purchase of inputs, like seeds, fertilizers, electricity etc. and farm assets like sickle, axe, spade, chopper, plough, tractor etc. The estimate of interest - the coefficient on Rythu variable is positive and significant in Columns (1) and (3). Column (1) shows that the total input expenditure per hectare increased by 34.8pp. Looking at the different expenditure items individually, I find that there is a significant increase in the expenditure on fertilizers and pesticides as shown in Table 2.9 in the appendix. Column (2) shows the effect on the probability of making either a) an expenditure on the purchase or repair or b) a sale of a farm asset while Column (3) shows the extent of expenditure made on the net purchase (purchase - sale) of farm assets conditional on a non-zero expense. These estimates show that while larger farmers were no more likely to make an investment, but those who did, almost doubled their expenditure on the purchase of productive assets for their farm business which was largely incurred on small tools (as reported in Table 2.10).

2.6.2 Effect on household labor allocation

Table 2.5 presents the estimated effect of the scheme on the labor allocation of the large farmers' households using individual-level analysis. An individual's principal activity status may be categorized into a complete set of mutually exclusive activities as reflected in Columns (1) to (10). I further classify the economic activities into the agriculture (Columns (1)-(3)) and non-agriculture sector (Columns (4-6)). Each column presents the estimates for the probability of an adult member of the household being engaged in the particular activity.

Columns (1) shows that the probability of being self-employed in the agriculture sector significantly increased by 8.5pp. Here, self employed includes those that work as own account workers, as employers or as helpers on their own farm.[23] At the same time, the probability of being engaged in education marginally reduced by 3.3pp.[24] These two results taken together, suggest that the larger farmers might be re-allocating their adult household members from education to work as helpers on their farm as result of receiving cash transfers under the scheme.[25] The probability of household members engaged in non-agriculture sector was unaffected.

2.6.3 Heterogeneity

So far, my main results have focused on large farmers[26] who received a sizable amount of cash transfers under RBS. I now shift focus to looking at the effect of the scheme on small farmers whose landholding size was less than 1 hectare during the two survey rounds. Table 2.6 presents the results for agricultural productivity for small farmers. Columns(1)-(3) use agricultural yield, sale rate (or local market price), and total value of output per hectare as the dependent variables. I find that the coefficient on Rythu is positive and significant only for the local market rate model showing that the rate at which small farmers sold their output in the market increased by 8.3pp

[23]Own account worker refers to those who operate on their own without hiring any labor or occasionally hiring a few laborers. This is in contrast to employers who hire laborers on a regular basis. Members of large farmers' households who're self-employed in agriculture are more likely to be engaged as helpers instead of as own-account workers on their farm compared to smaller farmers' household members.

[24]There are other estimates that are appreciable but insignificant as well as positive for agriculture labor in Column (2) and negative for domestic activity in column (9).

[25]There is some evidence to the negative effect of unconditional cash transfers on schooling. For instance, Ravetti (2020) shows that a third of studies on the effects of cash transfers on child labor report greater participation in child labor as a result of cash transfers.

[26]It is important to reiterate here my classification of farmers as "large" and "small" is for the sake of brevity and is as described in the empirical strategy in Section IV. It does not correspond to the official definition of small and large farmers based on landholding size. [19]

after the scheme was launched. This is similar to the estimates obtained for the large farmers. However, there is no significant effect on the crop yield or the total value of output per hectare.

This could be explained by the estimate for the input expenditure model in Column (1) of Table 2.7 where I find that the coefficient on Rythu is negative but insignificant. These results suggest that small farmers did not benefit from RBS in the way that large farmers did. Although, Column (3) on the amount of expenditure on the net purchase of farm assets shows positive and significant change for the small farmers similar to large farmers albeit smaller in magnitude. Given the lumpy nature of farm investment, these results would suggest plausible relaxation of credit constraints for the farmers as a result of cash transfers received under RBS.

Interestingly, the estimates for labor allocation of smaller farmers in Table 2.8 present a sharp contrast to the results for large farmers in Table 2.5. In Panel A, the coefficient of interest is negative and significant in Column (1) and (6), and positive and significant Column (2). This implies that the probability of being self-employed in agriculture as one's principal economic activity decreased by 7.2pp, the probability of being a regular salaried/wage worker in the non-agriculture sector decreased by 3.5pp, and the probability of working as an agricultural laborer increased by 16pp. On the other hand, Panel B Column (1) shows that the probability of being self-employed in agriculture as one's subsidiary activity increased by 5pp. These show that members of smaller farmers' households are shifting their labor from being farming and non-agricultural regular work to casual labor in the agriculture sector. This could be in response to the demand for labor by the larger farmers who are the main beneficiaries of RBS[27].

2.6.4 Robustness

Spillovers: Given the limited evidence of inter-sectoral re-allocation of labor from non-agricultural labor for small farmers as reported in Tables 2.8, I explore whether there were any spillover effects on the untreated households. This includes non-agricultural households as well as tenant farmers. The results for the tenant households are based on NSS data while the results for non-agricultural households are restricted to labor allocation only and are based on PLFS data[28]. These results are presented in Tables 2.11 to Table 2.14. However, I do not find any evidence of spillovers to either of these groups as the coefficient on Rythu remains insignificant across all columns in the two tables.

Falsification Test: Table 2.15 to Table 2.17 show the results from the falsification test by using 59th and 70th round of NSS SAS data for the years 2002-03 and 2012-13 respectively. I treat Telangana as treated in 2012-13. These results show that no significant difference in farm outcomes between Telangana and neighboring district large agricultural households in the period prior to the policy change. In terms of labor allocation, there was a negative effect on the casual agricultural labor and self employment in non-agricultural sector. However, the mean participation rate in these sectors is low and the results are significant only at 10% significance level.

[27]Although it is not possible to directly measure the number of laborers demanded or hired by the larger farm households, the results for input expenditure on human labor suggest that although the coefficient on RBS is positive, it is not significant

[28]For more details on the type of PLFS data, refer to Section IV

2.7 Conclusion

This study explores the effect of unconditional cash transfers to farmers on the extent of productive investment in agriculture and labor reallocation of household labor between on- and off-farm agricultural employment as well as inter-sectoral re-allocation. I conduct this exercise in the context of Telangana's Farmer Investment Support Scheme known as Rythu Bandhu Scheme. Rythu Bandhu Scheme offered unconditional cash transfer to farmers on a per hectare basis of land ownership at the beginning of each agricultural season to promote investment. The scheme allows me to examine the effect of different design elements including targeting, labeling, and size.

Using data on agricultural households and a difference-in-differences approach, I find that the positive productive effects are limited to large farmers who increase their expenditure on inputs and farm assets which is translated into higher yield and the total value of output produced. Small farmers also invest more in farm tools, however, they do not witness a similar improvement in yield. Further, transfers also encourage large farmers to reallocate labor from non-economic activities to working on own farm. On the other hand, small farmers switch from on-farm to off-farm agricultural employment. Finally, I find no spillover effects on tenant and non-agricultural households.

These results have important implications for policymakers. The positive impact of cash transfers on investment in productive capital suggests that credit and liquidity constraints exist, which are relaxed by timely cash transfers. Further, the reallocation of labor suggests the presence of labor market failure where small farmers are not able to find enough paid agricultural labor opportunities and pursue own farm production as an activity of last resort while the costs to monitor worker effort forces large farmers to rely on family labor. Finally, these heterogeneous effects suggest that the amount of transfer matters. It influences whether households increase their input spending and whether they dedicate more time to working on their own farms.

The main limitation of the study is that since the survey data pertains to the period immediately after the scheme launch, I'm only able to look at the short-term effects of the cash transfers to farmers and not the long-term impacts. For instance, it would interesting for future studies to explore if over the years, small farmers are able to save these transfers to invest more in inputs and farm assets to improve their output. Nonetheless, these results shed light on the effectiveness of cash transfers in addressing multiple market failures in the context of developing economies like India.

Figures

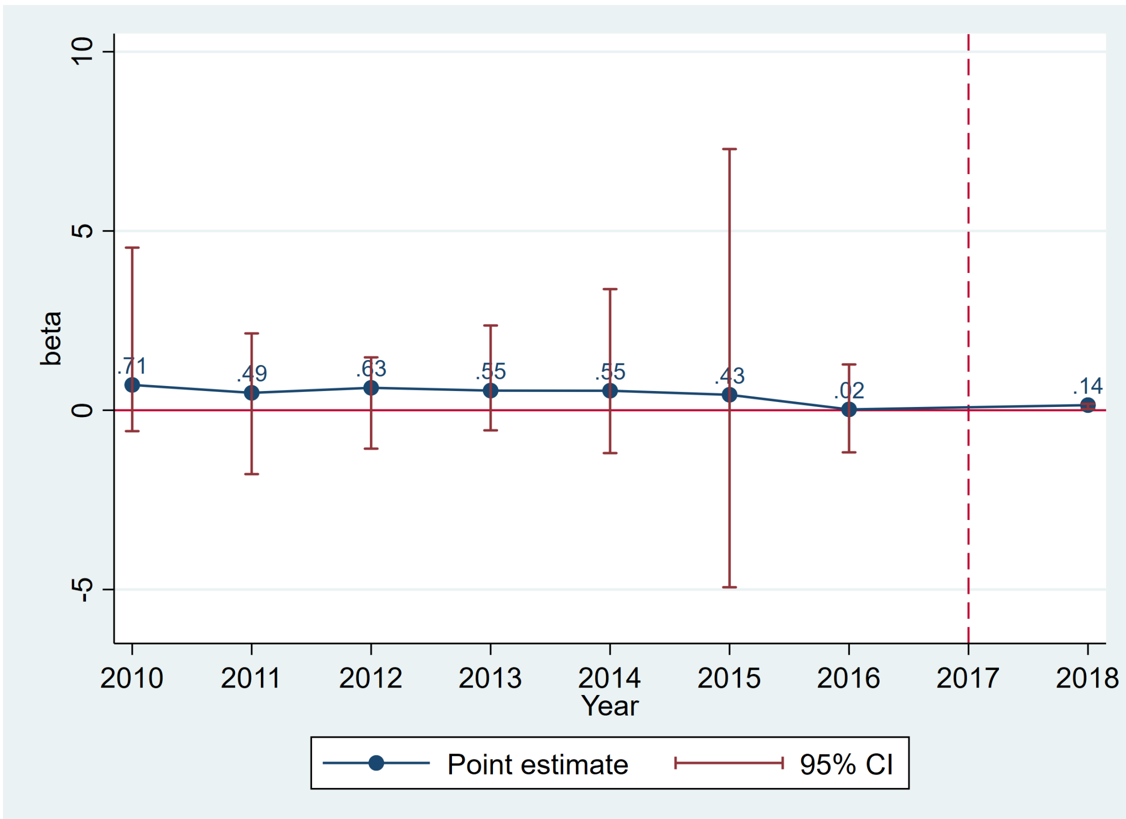

Figure 2.1: Event Study Estimates for Parallel-Trends Test

Notes:
Data Source: Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare.

Tables

	(1)
Land possessed (ha.)(%)	
$\leq$0.01	1.3
0.01-0.40	10.5
0.40-1.00	30.4
1.01-2.00	29.1
2.01- 4.00	21
4.01-10.00	6.5
10.00+	1.2
Land owned (ha.)	1.3
Land leased-in (ha.)	1.4
Tenant Holding (%)	25

Notes: The table presents summary statistics on different land related variable for an average agricultural household in Telangana and its neighboring districts which form my sample. These estimates are based on NSS SAS data for 2018-19 (Visit 1) using sampling weights.

Table 2.1: Table Summary Statistics on Land

	(1) ln(yield)
Rythu*2010	0.844
	(0.21)
Rythu*2011	0.746
	(0.18)
Rythu*2012	0.836
	(0.18)
Rythu*2013	0.694*
	(0.06)
Rythu*2014	0.703*
	(0.05)
Rythu*2015	0.771*
	(0.05)
Rythu*2016	-0.008
	(0.89)
Rythu*2018	0.094
	(0.23)
R-sq	0.656
Observations	3,967
Weather Control	Yes
District FEs	Yes
Crop-Season FEs	Yes
Year FE	Yes

Notes: The dependent variable is the natural logarithm of district-level crop-specific yield for a particular year and season. Rythu is a dummy variables which takes the value 1 for the treated state of Telangana and 0 for its neighboring districts from untreated states. The sample only includes the 16 important crops cultivated in the region. Each regression includes district, crop-season fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters), average and maximum monthly temperature (in degrees Celsius) for the respective season. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.2: DID Event Study Results for Yield

	(1) ln(yield)	(2) ln(rate)	(3) ln(total_value)
Rythu	0.107*	0.115*	0.231**
	(0.10)	(0.05)	(0.04)
Control mean	7.089	-3.338	3.824
R-sq	0.585	0.835	0.385
Observations	5,183	5,183	5,183
Addl. Control	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Crop-Visit FE	Yes	Yes	Yes
Round FE	Yes	Yes	Yes

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Rythu is a dummy which takes the value 1 for Telangana during 2018-19 and otherwise. Outcome variables are as follows: Column (1) log of quantity produced per hectare of land under cultivation of given crop, Column (2) log of local market price or the rate at which output produced was sold, and Column (3) log of total value of output produced per hectare where total value is the sum of quantity produced times rate, value of by-products, and pre-harvest sale. Value and price variables are measured in 1986-87 prices using visit-level Consumer Price Index for Agricultural Labor (CPI-AL). The unit of observation is at the crop-visit level. The sample is restricted to large farmers with land possession greater than 1 hectare. Only the main crops cultivated in Telangana and neighboring districts including rice, maize, jowar, pulses, sugarcane, chillies, turmeric, onion, oil seeds, and cotton are taken into account. Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression also includes district, round (year), and crop-visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.3: Program Effect on Agricultural Output: Large Farmers

	(1) ln(input_exp)	(2) farm_asset(=1)	(3) ln(asset_exp)
Rythu	0.348*	0.154	1.216*
	(0.06)	(0.34)	(0.07)
Control mean	3.201	0.506	0.459
R-sq	0.295	0.214	0.194
Observations	3,618	3,618	1,515
Addl. Control	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Visit FE	Yes	Yes	Yes
Round FE	Yes	Yes	Yes

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Rythu is a dummy which takes the value 1 for Telangana during 2018-19 and otherwise. Outcome variable is the log of expenditure (in 1986-87 rupees) on net purchase (purchase - sale) of (1) farm inputs and (3) assets per hectare of total land under cultivation respectively. Column (2) uses a dummy which takes the value 1 if a farm asset was bought or sold and 0 otherwise as the outcome variable. The unit of observation is at the cultivating household-visit level. The sample is restricted to large farmers with land possessed more than 1 hectare. Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression also includes district, round (year), and visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.4: Program Effect on Net Purchase of Farm Inputs and Assets

	Agriculture			Non-Agriculture						
	Self	Labor	Regular	Self	Labor	Regular	Unemployed	Education	Domestic	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rythu	0.085**	0.024	-0.003*	0.004	-0.007	-0.011	0.003	-0.033**	-0.100	0.018
	(0.04)	(0.38)	(0.05)	(0.42)	(0.32)	(0.45)	(0.38)	(0.05)	(0.22)	(0.62)
Control mean	0.716	0.058	0.00005	0.022	0.008	0.018	0.003	0.030	0.084	0.059
R-sq	0.138	0.042	0.011	0.023	0.019	0.044	0.029	0.062	0.211	0.036
Observations	14,390	14,390	14,390	14,390	14,390	14,390	14,390	14,390	14,390	14,390
Addl. Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Visit FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Each column presents the results of a separate regression. The dependent variable is a binary variable which takes the value 1 if a person is engaged in the particular activity during the reference period as their principal economic activity. The sample is composed of all adults aged 18 and above from large agricultural households. The unit of observation is a person. Rythu is a dummy variable equal to one for the state of Telangana during the 77th NSS SAS round i.e., July, 2018 - June, 2019 and 0 otherwise. Each regression includes district, visit (season) fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters) and maximum temperature (in degrees Celsius) along with worker controls including age, gender, caste, literacy, and head of household status. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.5: Program Effect on Labor Market Participation: Large Farmers

	(1) ln(yield)	(2) ln(rate)	(3) ln(total_value)
Rythu	0.085	0.083*	0.164
	(0.85)	(0.06)	(0.70)
Control mean	7.054	-3.358	3.780
R-sq	0.698	0.911	0.449
Observations	2,051	2,051	2,051
Addl. Control	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Crop-Visit FE	Yes	Yes	Yes
Round FE	Yes	Yes	Yes

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Rythu is a dummy which takes the value 1 for Telangana during 2018-19 and otherwise. Outcome variables are as follows: Column (1) log of quantity produced per hectare of land under cultivation of given crop, Column (2) log of crop price in the local market, and Column (3) log of total value of output produced per hectare where total value is quantity produced times rate plus with the value of by-products and pre-harvest sale. Value and price variables are measured in 1986-87 prices using visit-level Consumer Price Index for Agricultural Labor (CPI-AL). The unit of observation is at the crop-visit level and the sample is restricted to small farmers (land possession less than 1 hectare) and the 21 main crops cultivated in Telangana and neighboring districts including rice, maize, jowar, pulses, sugarcane, chillies, turmeric, onion, oil seeds, and cotton. Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression includes district, round (year), and crop-visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6: Program Effect on Agricultural Output: Small Farmers

	(1) ln(input_exp)	(2) farm_asset(=1)	(3) ln(asset_exp)
Rythu	-0.234	0.143	0.750*
	(0.66)	(0.19)	(0.08)
Control mean	3.184	0.425	0.577
R-sq	0.336	0.202	0.232
Observations	1,874	1,874	646
Addl. Control	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Season FE	Yes	Yes	Yes
Round FE	Yes	Yes	Yes

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Rythu is a dummy which takes the value 1 for Telangana during 2018-19 and otherwise. Outcome variable is the log of expenditure (in 1986-87 rupees) on net purchase (purchase - sale) of (1) farm inputs and (3) assets per hectare of total land under cultivation respectively. Column (2) uses a dummy which takes the value 1 if a farm asset was bought or sold and 0 otherwise as the outcome variable. The unit of observation is at the cultivating household-visit level. The sample is restricted to small farmers (land possessed less than 1 hectare). Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression also includes district, round (year), and visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7: Program Effect on Net Purchase of Farm Input and Assets: Small Farmers

	Agriculture			Non-Agriculture						
	Self	Labor	Regular	Self	Labor	Regular	Unemployed	Education	Domestic	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Principal Economic Activity									
Rythu	-0.072*	0.160*	0.001*	-0.0003	-0.010	-0.035*	-0.005	-0.003	-0.067	0.010
	(0.06)	(0.09)	(0.07)	(0.97)	(0.51)	(0.09)	(0.85)	(0.83)	(0.42)	(0.76)
Control mean	0.492	0.251	0.000	0.030	0.029	0.017	0.0002	0.018	0.120	0.039
R-sq	0.213	0.154	0.015	0.039	0.042	0.056	0.047	0.159	0.256	0.223
	Panel B: Subsidiary Economic Activity									
Rythu	0.051*	0.015	0.004	0.003	-0.011	-0.013	x	x	x	x
	(0.05)	(0.69)	(0.12)	(0.85)	(0.20)	(0.27)				
Control mean	0.223	0.171	0.001	0.012	0.009	0.003				
R-sq	0.094	0.123	0.009	0.040	0.030	0.031				
Observations	6,973	6,973	6,973	6,973	6,973	6,973	6,973	6,973	6,973	6,973
Addl. Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Visit FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Each column presents the results of a separate regression. The dependent variable is a binary variable which takes the value 1 if a person is engaged in the particular activity during the 6-month reference period. The sample is composed of all adults aged 18 and above. The unit of observation is a person. Rythu is a dummy variable equal to one for the state of Telangana during the 77th SAS round i.e., July, 2018 - June, 2019 and 0 otherwise. Each regression includes district, visit (season) fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters) and maximum temperature (in degrees Celsius) along with worker controls including age, gender, caste, literacy, and head of household status. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.8: Program Effect on Labor Market Participation: Small Farmers

2.8 Appendix

2.8.1 Individual Tests

	(1) Fertilizers	(2) Manure	(3) Pesticides	(4) Diesel	(5) Electricity	(6) Labor	(7) Animal	(8) Irrigation	(9) Repairs	(10) Interest	(11) Machinery	(12) Rent	(13) Other
Rythu	0.220*	0.014	0.493*	-0.767	-0.030	0.302	-0.235	0.555	-0.046	0.593	-0.086	0.361	-0.214
	(0.07)	(0.95)	(0.05)	(0.13)	(0.77)	(0.18)	(0.35)	(0.38)	(0.73)	(0.18)	(0.64)	(0.30)	(0.49)
dep. mean	1.847	0.818	1.374	0.532	-0.357	1.913	0.795	-0.218	-0.552	1.131	0.849	2.870	-0.247
N	3,436	1,285	2,899	657	1,318	3,456	1,235	507	1,201	902	2,769	602	2,528
R-sq	0.261	0.166	0.252	0.355	0.411	0.305	0.177	0.226	0.211	0.188	0.398	0.386	0.145

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Each column presents the results of a separate regression. The dependent variable is log of expenditure on a particular input conditional on spending on the input. Rythu is a dummy variable equal to one for the state of Telangana during the 77th SAS round i.e., July, 2018 - June, 2019 and 0 otherwise. Each regression includes district, visit (season) fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the season along with household controls including size and caste. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.9: Program Effect on Input Expenditure: Large Farmers

	Land	Building	Livestock	Tools	Tractor	Pump	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rythu	0.455	-25.339	0.141	0.554*	-1.104	-0.320	0.215
	(0.87)	(0.10)	(0.83)	(0.08)	(0.51)	(0.85)	(0.83)
Control mean	2.140	1.328	2.761	-1.058	1.286	0.951	-0.276
Observations	79	27	121	1,286	86	346	108
R-sq	0.443	0.850	0.418	0.127	0.404	0.241	0.615

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Each column presents the results of a separate regression. The dependent variable is log of net expenditure on a particular asset conditional on spending on the asset. Rythu is a dummy variable equal to one for the state of Telangana during the 77th SAS round i.e., July, 2018 - June, 2019 and 0 otherwise. Each regression includes district, visit (season) fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters) and average monthly temperature (in degrees Celsius) for the season along with household controls including size and caste. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.10: Program Effect on Net Purchase of New Asset Purchase: Large Farmers

2.8.2 Subsidiary Activity of Large Farmers

	Agriculture			Non-Agriculture		
	Self	Labor	Regular	Self	Labor	Regular
	(1)	(2)	(3)	(4)	(5)	(6)
Rythu	0.001	0.121	-0.008	0.006	-0.003	-0.002**
	(0.94)	(0.21)	(0.85)	(0.47)	(0.35)	(0.02)
Addl. Control	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.066	0.218	0.000	0.015	0.008	0.001
R-sq	0.037	0.121	0.017	0.018	0.025	0.006
Observations	14,390	14,390	14,390	14,390	14,390	14,390

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Each column presents the results of a separate regression. The dependent variable is a binary variable which takes the value 1 if a person is engaged in the particular activity during the reference period as their subsidiary economic activity. The sample is composed of all adults aged 18 and above. The unit of observation is a person. Rythu is a dummy variable equal to one for the state of Telangana during the 77th SAS round i.e., July, 2018 - June, 2019 and 0 otherwise. Each regression includes district, visit (season) fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the season along with worker controls including age, gender, caste, literacy, and head of household status. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Subsidiary Labor Market Participation: Large Farmers

2.8.3 Spillover

	(1) ln(yield)	(2) ln(rate)	(3) ln(total_value)
Rythu	-0.077	0.015	-0.080
Addl. Control	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Crop-Visit FE	Yes	Yes	Yes
Round FE	Yes	Yes	Yes
Control mean	7.981	-3.692	4.324
Observations	940	940	940
R-sq	0.797	0.899	0.594

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Rythu is a dummy which takes the value 1 for Telangana during 2018-19 and otherwise. Outcome variables are as follows: Column (1) log of quantity produced per hectare of land under cultivation of given crop, Column (2) log of crop price in the local market, and Column (3) log of total value of output produced per hectare where total value is quantity produced times rate plus with the value of by-products and pre-harvest sale. Value and price variables are measured in 1986-87 prices using visit-level Consumer Price Index for Agricultural Labor (CPI-AL). The unit of observation is at the crop-visit level and the sample is restricted to tenant (do not own any land) farmers and the 21 main crops cultivated in Telangana and neighboring districts including rice, maize, jowar, pulses, sugarcane, chillies, turmeric, onion, oil seeds, and cotton. Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression includes district, round (year), and crop-visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.11: Program Effect on Agricultural Output: Tenant Farmers

	(1) ln(input_exp)	(2) farm_asset(=1)	(3) ln(asset_exp)
Rythu	0.120	0.562	2.585
	(0.54)	(0.27)	(0.32)
Addl. Control	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Season FE	Yes	Yes	Yes
Round FE	Yes	Yes	Yes
Control mean	4.263	0.488	0.206
Observations	924	924	376
R-sq	0.350	0.197	0.463

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Rythu is a dummy which takes the value 1 for Telangana during 2018-19 and otherwise. Outcome variable is the log of expenditure (in 1986-87 rupees) on net purchase (purchase - sale) of (1) farm inputs and (3) assets per hectare of total land under cultivation respectively. Column (2) uses a dummy which takes the value 1 if a farm asset was bought or sold and 0 otherwise as the outcome variable. The unit of observation is at the cultivating household-visit level. The sample is restricted to tenant (do not own any land) farmers. Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression also includes district, round (year), and visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.12: Program Effect on Net Purchase of Farm Input and Assets: Tenant Farmers

	Agriculture			Non-Agriculture			
	Self (1)	Labor (2)	Regular (3)	Self (4)	Labor (5)	Regular (6)	Other (7)
Rythu	-0.195	0.147	-0.000	0.088	0.003	-0.014	-0.127
	(0.64)	(0.31)	(0.72)	(0.59)	(0.49)	(0.55)	(0.68)
Addl. Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Visit FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.533	0.158	0.005	0.049	0.017	0.047	0.191
Observations	2,975	2,975	2,975	2,975	2,975	2,975	2,975
R-sq	0.237	0.081	0.001	0.218	0.055	0.046	0.325

Notes: The results presented in the table are based on the 70th and 77th NSS SAS survey data for the years 2012-13 and 2018-19 respectively. Each column presents the results of a separate regression. The dependent variable is a binary variable which takes the value 1 if a person is engaged in the particular activity during the reference period. The sample is composed of all adults aged 18 and above from tenant households. The unit of observation is a person. Rythu is a dummy variable equal to one for the state of Telangana during the 77th SAS round i.e., July, 2018 - June, 2019 and 0 otherwise. Each regression includes district, visit (season) fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters) and maximum temperature (in degrees Celsius) along with worker controls including age, gender, caste, literacy, and head of household status. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.13: Program Effect on Labor Market Participation: Tenant Farmers

	Agriculture			Non-Agriculture						
	Self (1)	Labor (2)	Regular (3)	Self (4)	Labor (5)	Regular (6)	Unemployed (7)	Education (8)	Domestic (9)	Other (10)
Rythu	0.014	0.008	0.072	0.013	-0.019	-0.021	0.001	-0.065	-0.023	0.021
	(0.49)	(0.33)	(0.38)	(0.45)	(0.18)	(0.30)	(0.81)	(0.37)	(0.33)	(0.16)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FY-Q FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Addl. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.027	0.003	0.063	0.162	0.156	0.101	0.009	0.268	0.166	0.045
Observations	5,691	5,691	5,691	5,691	5,691	5,691	5,691	5,691	5,691	5,691
R-sq	0.055	0.023	0.082	0.133	0.135	0.134	0.036	0.407	0.469	0.032

Notes: Each column presents the results of a separate regression. The dependent variable is a binary variable which takes the value 1 if a person is engaged in the particular activity during the reference week. The sample is composed of all individual between the age of 14 and 60 belonging to households classified as non-agricultural. The unit of observation is a person. Rythu is a dummy variable equal to one for the state of Telangana during the July, 2018 - June, 2019 PLFS round and 0 otherwise. Each regression includes district, year-quarter fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in meters) and maximum temperature (in degrees Celsius) along with worker controls including age, gender, caste, and literacy status. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.14: Program Effect on Labor Market participation: Non-Agricultural Households

2.8.4 Falsification Test

	(1) ln(yield)	(2) ln(total_value)
Rythu	-0.031	-0.075
	(0.93)	(0.65)
Addl. Control	Yes	Yes
District FEs	Yes	Yes
Crop-Visit FE	Yes	Yes
Round FE	Yes	Yes
Control mean	7.166	3.617
Observations	7,583	7,583
R-sq	0.503	0.413

Notes: The results in the table are based on 59th and 70th round of NSS data for the years 2002-03 and 2012-13 respectively. For this falsification test, Rythu is a dummy which takes the value 1 for Telangana in 2012-13 round and 0 otherwise. Outcome variables are as follows: Column (1) log of quantity produced per hectare of land under cultivation of given crop, Column (2) log of total value of output produced per hectare where total value is quantity produced times rate plus with the value of by-products and pre-harvest sale. Value and price variables are measured in 1986-87 prices using visit-level Consumer Price Index for Agricultural Labor (CPI-AL). The unit of observation is at the crop-visit level and the sample is restricted to large farmers and the 21 main crops cultivated in Telangana and neighboring districts including rice, maize, jowar, pulses, sugarcane, chillies, turmeric, onion, oil seeds, and cotton. Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression includes district, round (year), and crop-visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.15: Falsification Test for Agricultural Output: Large Farmers

	(1) ln(input_exp)	(2) farm_asset(=1)	(3) ln(asset_exp)
Rythu	0.002	-0.031	0.361
	(0.40)	(0.67)	(0.41)
Control mean	0.876	0.149	1.072
Observations	5,679	5,679	1,616
R-sq	0.013	0.136	0.201
Addl. Control	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Season FE	Yes	Yes	Yes
Round FE	Yes	Yes	Yes

Notes: The results in the table are based on 59th and 70th round of NSS data for the years 2002-03 and 2012-13 respectively. For this falsification test, Rythu is a dummy that takes the value 1 for Telangana in 2012-13 round and 0 otherwise. Outcome variable is the log of expenditure (in 1986-87 rupees) on net purchase (purchase - sale) of (1) farm inputs and (3) assets per hectare of total land under cultivation respectively. Column (2) uses a dummy which takes the value 1 if a farm asset was bought or sold and 0 otherwise as the outcome variable. The unit of observation is at the cultivating household-visit level. The sample is restricted to large farmers. Each regression includes controls for household size and caste along with district-level total Kharif (southwest monsoon) rainfall (in meters) and maximum monthly temperature (in degrees Celsius) for the visit (season). Each regression also includes district, round (year), and visit fixed effects. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.16: Falsification Test for Net Purchase of Farm Input and Assets: Large Farmers

	Agriculture			Non-Agriculture			
	Self	Labor	Regular	Self	Labor	Regular	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rythu	0.062	-0.071*	0.004	-0.029*	-0.005	0.001	0.038
	(0.11)	(0.06)	(0.34)	(0.07)	(0.36)	(0.80)	(0.26)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FY-Q FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Addl. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.396	0.070	0.002	0.022	0.005	0.014	0.484
Observations	14,734	14,734	14,734	14,734	14,734	14,734	14,734
R-sq	0.146	0.094	0.014	0.024	0.017	0.027	0.229

Notes: The results in the table are based on 1st and 2nd round of PLFS survey data for the years 2017-18 and 2018-19 respectively. Each column presents the results of a separate regression. The dependent variable is a binary variable which takes the value 1 if a person is engaged in the particular activity during the reference week. The sample is composed of all working age individuals from non-agricultural households. The unit of observation is at the individuals level. Rythu is a dummy variable equal to one for the state of Telangana during the July, 2018 - June, 2019 PLFS round and 0 otherwise. Each regression includes district, year, visit fixed effects. Each regression controls for time-varying district variables i.e. total southwest (Kharif) rainfall (in mm) and maximum temperature (in degrees Celsius) along with worker controls including age, gender, caste, and literacy status. All estimates are computed using sampling weights. Standard errors are cluster bootstrapped at state level and wild cluster p-value is estimated based on 999 replications using Webb weights (shown in parentheses). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.17: Falsification Test for Labor Market participation: Large Farmers

3

Women Leaders and Lobbying for Development Funds: Evidence from India

3.1 Introduction

The prevalence of gender imbalance in positions of leadership and power, whether it be on corporate boards or in political institutions, is a worldwide phenomenon. Quotas have been increasingly used to address this gender gap and improve the representation of women in the public sphere. This is particularly true in the political arena. Many countries including India have introduced constitutional amendments and legislative orders mandating that a certain percentage of elected representatives be women. However, quotas alone may not be enough to remove the barriers that deter women from entering and performing well in the politics and may well end up creating a new glass ceiling for women leaders.

Set in the context of the Indian state of Rajasthan, this paper explores the differential access to development funds by village councils that are reserved for women and those that are not. In a 1992 constitutional amendment, the Government of India set up and devolved significant powers to a three-tiered local administration and reserved one-third of all its member and chairperson seats for women. In this study, I focus on the lowest tier of the local government present at the village level known as Gram Panchayats (henceforth GPs). GPs play a crucial role in the last-mile delivery of public goods and services, and welfare programs. Over time, while there has been a considerable transfer of functions and functionaries to the GPs, this has not been matched by an equivalent transfer of finances and GPs are still largely dependent on the state government for resources. Therefore, in a male-dominated political and bureaucratic system and a male-biased society, women Sarpanches might find it difficult to access discretionary funds and funds contingent on subjective official evaluation.

To test my hypothesis, I use a GP-level panel data set on the loans released under Rural Infrastructure Development Fund (RIDF), a large public sector capital investment scheme targeted at rural areas. Reservation data for three GP terms[1]:

[1] A GP is elected for a five year term

2005, 2010, and 2015 is combined with RIDF loan data for the same period. The randomized nature of women's reservation for the position of a GP's chairperson, known as Sarpanch, provides an ideal setting to estimate the causal impact of having reservation for a woman Sarpanch by comparing the means of relevant outcomes between GPs that were reserved for women and those that were unreserved. First, I estimate a linear probability model and compare the probability of a GP receiving an RDIF loan as the reservation status changes over time. Second, conditional on a GP receiving a loan, I compare the amount of loan disbursed as a fraction of the total loan sanctioned under different reservation status.

My main finding is that the coefficient on women reservation dummy for the probability of receiving a loan is negative and statistically significant. This suggest GPs reserved for a woman Sarpanch are less likely to receive an RDIF loan than the unreserved, mostly male Sarpanch led, GPs. Looking at the GPs that received a loan, there is also a significant difference in the amount of loan disbursed as a share of the amount of loan sanctioned for the intended project between reserved and unreserved GPs. I find that GPs reserved for women Sarpanch have greater rate of loan disbursal towards the implementation of the project. These results are robust to alternative empirical specifications.

To identify the underlying mechanism driving these results, I explore the role of a difference in Sarpanch characteristics, distance to the district headquarter, and social context. I find controlling for Sarpanch age, education, and occupation, does not alter the results without any controls[2]. Further, I do not find similar results when

[2]The data on Sarpanch characteristics is only available for one GP term. Based on this reduced sample size, I find that while the coefficient on women's reservation dummy for the probability of getting an RIDF loan is still negative, it is not statistically significant. However, the coefficient of interest remains positive and significant for the rate of loan disbursal with or without controls.

I look at the Indian state of Kerala instead. Kerala has remained a top-performing state on various indices[3] that look at the status of women in terms of access to education, security, financial inclusion and so on. Finally, I examine the role of social constraints on women's mobility by using GP distance to the district administration's headquarters as a proxy. I find that negative effect of having a woman Sarpanch on the likelihood of getting a loan is attenuated if GPs that are located closer to the district HQ. Taken together, these results are suggestive of both supply and demand side barriers that hinder women Sarpanch's ability to lobby for development funds.

This paper contributes to two main strands of literature. First, it builds on the existing work on the impact of female leadership which has been studied in the context of corporate directorships (e.g., Matsa and Miller (2011)) and in the political context (e.g., Ferreira and Gyourko (2014); Clots-Figueras (2011)). These papers examine the role of supply-side factors such as differences in personality and preferences as well as demand-side factors such as discrimination from male colleagues to explain the gap in the number of female leaders and their performance.

Secondly, this paper also offers new evidence on the impact of affirmative action. In particular, the impact of political reservation for women has been widely studied in the last two decades, especially in the Indian context. These studies have looked at broad set of outcomes such as public goods provision (Chattopadhyay and Duflo, 2004), targeting (Bardhan et al., 2010), crime (Iyer et al., 2012), corruption (Afridi et al., 2017), neonatal mortality (Bhalotra and Clots-Figueras, 2014) and so on. However, their findings offer mixed results[4] and the financial management aspect

[3]Some examples include Ministry of Education's 2020-21 Gender Parity Index, Hindustan Times' 2017 Women Empowerment Index, McKinsey Global Institute's 2019-20 Women Peace and Security Index.

[4]For instance, Chattopadhyay and Duflo (2004) show that women Sarpanch in Rajasthan and

is relatively unexplored. With this paper, I am able to contribute towards filling this gap in the literature.

The remainder of the paper is organized as follows. Section II describes the Panchayat system and the working of RIDF scheme. Section III discusses the data and Section IV outlines the estimation methodology. The main results are presented in Section V. Section VI looks at possible mechanisms and Section VII discusses the findings in this paper. Section VIII concludes.

3.2 Background

3.2.1 India's Panchayati Raj System

The Panchayati Raj system in India is a form of decentralized rural administration, established pursuant to the 73rd amendment to the Constitution of India in 1992[5]. The Act laid out provisions[6] for the institution of a three-tiered local self-government called Panchayats[7] in rural areas. These three levels comprise of Gram

West Bengal are more likely to invest in public goods that reflect the preferences of their female electorate such as drinking water. But these findings are not corroborated by results from Ban and Rao (2008) who look at four South Indian states and find no significant difference between the Panchayat activities of GP reserved for women and unreserved. Further, these activities were not in line with Sarpanch preferences.

[5]Given the quasi-federal nature of Indian Government, following the enactment of the Constitution (Seventy-third Amendment) Act, 1992, all state governments passed their respective Panchayati Raj Acts to devolve powers and responsibilities to the newly established Panchayati Raj Institutions (PRIs).

[6]Part IX of the Constitution put in place by the 73rd Amendment outlines the guidelines regarding the composition, reservation, duration, and powers, among other aspects, regarding the functioning of these Panchayats.

[7]Traditional village panchayats composed of village elders for the purpose of dispute resolution and the preservation of group interest have a long history in South Asia. Another form of such village councils based on caste identity known as Khap panchayats are prevalent in Northern India. However, the legal status and powers of these councils remained unclear and informal.

Panchayat (or GP) at the village level[8], Panchayat Samiti at the block level and Zilla Parishad at the district level.

All Panchayat members are directly elected by the people from the territorial constituencies in the Panchayat area for a term of five years[9]. The Chairperson of the Panchayat is elected by, and from amongst, the elected members at the block and district level. The Chairperson of the Panchayat at village level or GP, known as the Sarpanch, is generally elected directly by the people. There is also provision for reservation of council seats and council head positions for members of disadvantaged castes, and women.

States have the power to devolve 29 functional areas, as listed in the Eleventh Schedule in the Constitution of India, to the Panchayati Raj Institutions (PRIs). This empowers the PRIs to prepare plans for and carry out the implementation of schemes for economic development and social justice in the areas under their jurisdiction. At the GP level, this involves recognizing local needs and planning[10] for the provision of local infrastructure, generating awareness and social mobilization of public programs, identification of eligible beneficiaries, implementation of, maintaining record of and monitoring the progress of development works, and grievance redressal. Panchayats at the higher levels play a more supervisory role by conducting surveys, preparing reports, thereby acting as an information bridge between the GP and the State.

To carry out their functions, GPs derive funding from three main sources- grants from the center and the state as well as their own resources [11]. Although a

[8] A GP generally encompasses 5-15 villages.

[9] State Election Commissions are set up to conduct regular, free, and fair elections to the PRIs.

[10] GPs operate on a participatory development principle which can be seen in action during the bi-annual village meetings called Gram Sabha.

[11] A State Finance Commission is periodically constituted to determine the allocation of financial resources between the State and the PRIs, and between the different levels of the PRIs.

GP has the power to levy and collect taxes, duties, and fees, these form a meagre 1% (Reserve Bank of India, 2024) of their total GP revenue[12]. Consequently, GPs rely heavily on central and state grants-in-aid for their funding. However, the Sarpanch can lobby their local parliamentarian, block and district officials, specific government departments, and the private sector for additional funds.

3.2.2 Reservation for Women in Panchayats

The 73rd Amendment stipulates the reservation of seats for the position of Panchayat members and the Chairperson for women as well as for individuals of disadvantaged groups namely-the Scheduled Castes (SCs), and the Scheduled Tribes (STs). The proportion of seats reserved for women was to be no less than one-third of the total number of such positions while the seats reserved for SC and ST individuals was to be proportional to their share in that State's population.

Modifications have since been made to these provisions as States have passed and amended their respective Panchayati Raj Acts. Since 2006 many states have increased the reservation of women from 33% to 50%. For instance, Rajasthan State Legislature passed 'The Rajasthan Panchayati Raj (Second Amendment) Act, 2008' raising the reservation for women to 50% which has been incorporated in the principal act 'The Rajasthan Panchayati Raj Act, 1994'[13].

The exact procedure followed to implement the reservation was left to the State Legislature. In Rajasthan, the reservation for SC, ST is made first, in that

[12] GPs face strong opposition to agricultural taxation from the rich farmers' lobby groups (Ghatak and Ghatak, 2002).

[13] Further, the Act provides for reservation for individuals belonging to Other Backward Castes (OBCs) in addition to SCs and STs.

order, at each Panchayati Raj level. The number of seats reserved for SC (ST) is proportional to their population and are allocated to Panchayat constituencies (or wards) arranged serially in decreasing order of their SC (ST)[14] population[15]. Next, one-third of the seats reserved for the SC (ST) are also randomly reserved for the women belonging to the caste by selecting every third GP in that list. This women reservation rule of random selection is also applicable to seats that are not reserved for any particular caste so that one-third of all the council seats and Sarpanch positions are reserved for women[16]. Table 2 shows that the reservation process is adhered to strictly as all the GPs where the Sarpanch's position was reserved for women was, in fact, filled by a woman [17].

3.2.3 Rural Infrastructure Development Fund

In 1995, the Government of India set up the Rural Infrastructure Development Fund (RIDF) with an initial corpus of 20 billion rupees at the National Bank for Agriculture and Rural Development (NABARD). The objective of RIDF was to boost public sector capital investment in rural infrastructure by providing loans to state governments and state-owned corporations at concessional rates. Beginning year 1999, GPs, self-help groups, and NGOs became eligible for RIDF loans, provided the

[14] The Rajasthan Panchayati Raj Act also provides for the reservation of seats for individuals belonging to Other Backward Castes (OBCs) which is carried out by draw of lots after the allocation of reserved seats for SCs and STs.

[15] This process continues to be operated serially from where the selection ended in the preceding election until the list is exhausted.

[16] GPs reserved in the first general election are excluded while drawing lots for such reservation in succeeding elections till the cycle is completed

[17] There are reports that some women Sarpanches act as surrogates on behalf of their male family members (mostly husbands). Beaman er al., (2010) find that female politicians were more likely to be encouraged by their husbands to stand for GP elections and thereafter, received their help in carrying out their duties.

projects were submitted through the state finance department and the state government remained the main guarantor of the loan.

Resources to RIDF are supplied by scheduled commercial banks to meet the shortfall in their priority sector lending target, set by the Reserve Bank of India[18]. The corpus of a each tranche of RIDF is decided by the Government of India and this annual corpus is allocated among states based on a set of norms as prescribed by NABARD. A total 681,407 projects valued at 3,661 billion rupees have been sanctioned to state governments as of 31 July 2020 and RIDF is currently in disbursement of its XXVI Tranche.

Initially, RIDF capital was earmarked for ongoing irrigation projects that remained incomplete for the lack of financial resources. Later, these funds were made available for new projects and their coverage was enhanced to include 37 activities broadly classified under 3 heads: agriculture and allied sector (which subsumed irrigation projects), rural connectivity, and social sector.

Relevant state government departments must submit their project proposals directly to NABARD after getting the approval of the District Planning Committee with a copy to the finance department. GPs can approach the Panchayat Raj department at the district level with their proposal for consideration. Eligible projects are then submitted by the Finance departments on behalf of the State Governments to NABARD for their due appraisal and sanction. Cost estimates are based on the latest schedule of Rates (SoR). Once a project is sanctioned, the loan amount is released in installments on reimbursement basis and is conditional on timely progress made in the implementation of the project. In the case of GPs, while allocated funds

[18]Banks are required to make a minimum of 40% of their total loans to economically weak sectors such as agriculture and allied, medium to small industries, and education.

get parked in the panchayat's account with the nearby bank branch, any withdrawal requires approvals from the block and district authorities.

Since the district authorities play a key role in the process of applying for and utilizing RIDF funds, the likelihood that a GP receives a loan depends on the ability of its Sarpanch to effectively lobby the higher level bureaucrats. Lobbying entails traveling to the district headquarters which requires time and money. The cost is even greater for women Sarpanches who face societal constraints on their mobility. This is best captured by a quote from a female Sarpanch (IndiaSpend, 2018).

> We have no funds to build [local infrastructure]. Most of the big scheme funds as well as NABARD funds are handled by the assistant director of panchayats. We need to regularly show our face to get funds. Men go directly to him, sit with him for a long time and ensure funding. We can't.

3.3 Data

This section describes how I construct a GP-level dataset for Rajasthan by utilizing administrative data on RIDF loans, GP reservation status, and Sarpanch characteristics as well as the process of combining them all together.

RIDF: The data on RIDF loans is extracted from NABARD's social monitoring reports that contain information on the universe of projects sanctioned under RDIF. NABARD's regional offices and government functionaries at the state level and at the district level provide the information furnished in these reports. These reports are compiled separately for each state and are made publicly available on

NABARD's website. For a given project, they provide loan details including project district, block or village or GP, sector, details, implementing department, estimated cost, amount of loan sanctioned, date of sanction, expected date of completion, and the amount of loan disbursed till date.

Of the total 42,724 projects, completed or ongoing, in the state of Rajasthan, around 63 percent are related to the construction of rural roads and bridges[19]. However, in most cases it is not possible to identify the GPs benefiting from these projects from the location information available in the data. This is either due to the multi-village nature of these projects or the inch-perfect nature of the location detail provided in the data. Therefore, I exclude this sectors from my analysis.

I restrict my sample to the other important sectors: education, health, and agriculture-allied. These involve construction of government schools, health centers, and agriculture extension centers (henceforth referred to as KSK-VKC-LRIC)[20]. Together, projects under these sectors account for 25 percent of all the projects sanctioned under RDIF; education accounts for 10 percent, health for 4 percent, and KSK-VKC-LRIC for 11 percent of all the projects. In terms of share in the total value of loans sanctioned under RDIF, the relative importance of these sectors is fairly similar. Roads account for 34 percent of total loan value, irrigation's share is 14 percent, education is at 3 percent, health is at 5 percent and KSK-VKC-LRIC is at 2 percent[21]. Table 1 presents the summary statistics for the loans data used in

[19] Another important sector is irrigation, involving the construction of anicuts and water harvesting structures, which accounts for additional 7 percent of all the projects projects.

[20] KSK stands for Krishi Sewa Kendra which are Agricultural Technology Information Centres , VKC stands for Village Knowledge centers, and LRIC stands for Land Records Information Center. These centers provide farmers access to subsidized seeds, fertilizers, latest information, and access to land records, among other agricultural services.

[21] An important sector in terms of loan value is the provision of rural drinking water supply accounting for 33 percent of total loan value. However, all these water supply projects are medium-

this paper.

Besides the name of the district, information about the location of these projects is limited. In most cases, the data contains information on either the name of the block or the GP or the village in which the project was implemented. Cases where the smallest administrative unit identified in the data is the project block are dropped from the final sample. To identify a GP if there are multiple GPs by the same name in a district, one needs information about the name of the corresponding block[22]. Therefore, it is not always possible to uniquely identify the affected GP. Such cases constitute around 6 percent of the sample and are dropped during estimation. My final RDIF sample consists of 6282 projects covering 5069 GPs over all 33 districts of Rajasthan.

Reservation: Information on the reservation status of the Sarpanch position in GPs is collected from Rajasthan State Election Commission's website[23], for the relevant GP terms i.e., 2005, 2010, and 2015. These provide information on the GP's district, block, and reservation status along with the elected Sarpanch's name, caste, and gender. Table 2 shows that there is perfect enforcement of the reservation mandate at the GP level. At the same time, there's few women Sarpanches in the unreserved seats.

Sarpanch Characteristics: To test the robustness of my main results, I also control for the effect of other observable Sarpanch characteristics. For this purpose, I obtain data on Sarpanch age, education, and occupation as filed by the candidate on

to large-scale, multi-location works where it is difficult to identify affected GPs. Finally, loans sanctioned for forest development are valued at 2.5 percent, consisting of 3 big projects.

[22]Likewise, when a common village name is available, one needs information about the block and/or GP name to uniquely identify the affected GP.

[23]The website is http://www.rajsec.rajasthan.gov.in

their affidavits during the 2010 GP election. This data was collected by filing Right to Information (RTI) requests with the Election Commission in Rajasthan and manually inputted based on detailed official records[24] as reported by district administrations to the election commission by Das et al., (2023).

Combining Datasets: In order to create a GP-level dataset required combining the data on loan, reservation, and Sarpanch based on GP ID. However, neither of these files have a unique GP ID code. Further, the transliteration of GP names from Hindi to English results in the same GP name being spelled in different ways. To deal with this issue, I employ fuzzy matching to link these files together. I am able to successfully match 96% of GPs that received an RIDF loans and a further 92% to their respective Sarpanch data[25].

Matching GPs to villages: I link the GPs to their villages using a 2020 version of GP-village mapping file obtained from Local Government Directory website[26] of Ministry of Panchayati Raj[27]. Again, this is carried out by fuzzy matching on GP names in the two datasets. In doing so, I am able to obtain the unique village codes from the 2001 and 2011 Census of India.

Census: In order to test the exogeneity of the reservation process, I compare the characteristics of villages under GPs which are randomly reserved for female leaders versus those that are not. For this, I use Census of India data for the years

[24]Some Election records had gone missing when the authors inputted the data in 2016 while other were missing information on individual variables. For instance, the records for the districts of Bikaner and Sirohi are completely missing. These observations form 27.5% of the ttoal GPs in 2010, are evenly distributed between reserved and unreserved GPs, and are dropped from the analysis.

[25]Match rate corresponds to the 2010 GP election cycle.

[26]Accessible at http://lgdirectory.gov.in/.

[27]Due to possible re-assignment of villages across GP between 2001 census data and the more recent GP-village mapping data, the distance measure is likely to be noisy and the village characteristics balance test is imperfect.

2001 and 2011 from India Village-Level Geospatial Socio-Economic Data Set [28] and Socioeconomic High-resolution Rural-Urban Geographic Data set (SHRUG) (Asher et al., 2021) respectively. In particular, I use population numbers from the Primary Census Abstract and data on village-level infrastructure from the Village Amenities component. I do this by merging on unique village census codes obtained in the step above and that are also available in the SHRUG dataset.

Distance: I look at the heterogeneity of my main results with GP's distance to the district headquarter. To do this, I obtain the village level shapefile from SHRUG (Asher et al., 2021) and 2024 version district headquarter shapefile from Survey of India's Onlinemaps portal[29]. Next, I use QGIS software to calculate the distance in kilometers between the centroids of villages to their corresponding district headquarters. Again, since the SHRUG village shapefile contains village census codes, it is easy to combine the distance measure to the GP-village level dataset.

3.4 Estimation Strategy

The goal of this paper is to examine the effect of reservation of the position of Sarpanch for women on the GP's RIDF loan outcome. Since the reservation for women is carried out randomly, the basic empirical strategy is pretty straightforward. Comparing the difference in the mean outcomes of the GPs reserved for women and those that are unreserved would give us the average treatment effect of reservation for women.

[28] The data set is a digitization of maps from the 2001 Survey of India linked to village-level 2001 census information, published by the NASA Socioeconomic Data and Applications Center (SEDAC).

[29] This file was missing the HQ for Pratapgarh district. I obtained the GPS coordinates for Pratapgarh using GoogleMaps.

My preferred empirical strategy exploits additional features of the reservation process and the available data of RIDF loans. Firstly, GPs reserved for women are randomly selected following caste-based reservation. Secondly, both the reservation and the RIDF loan approval process are carried out at the district level. Finally, GP-level RIDF loans data is available for the period covering three election cycles and provides information on the type of infrastructure (or "sector") for which the loan was made[30].

Taking into account these features, I employ a two-way fixed effects regression analysis. The estimating equation is of the following form:

$$Y_{g,s,t} = \alpha_s + \tau_t + \theta_g + \beta R_{g,t} + \gamma C_{g,t} + \delta R_{g,t} * C_{g,t} + \epsilon_{g,s,t} \tag{3.1}$$

where $Y_{g,s,t}$ is outcome of interest for sector s in GP g in term t. $R_{g,t}$ is an indicator variable which takes the value 1 if the Sarpanch position in the GP was reserved for a woman and 0 otherwise. Likewise, $C_{g,t}$ is an indicator variable that takes the value 1 if the Sarpanch position was reserved for a individual from a disadvantaged caste (i.e OBC, SC, ST) and 0 otherwise. $\epsilon_{g,s,t}$ denotes standard errors which are clustered at the block level to account for possible correlation between GPs under a block administration.

To further allay concerns regarding the randomness of the reservation process, I control for GP-specific unobservables, by including θ_g which are GP fixed effects. τ_t are GP term fixed effects that capture common period-specific shocks. Finally, I include α_s which is sector fixed effects when the outcome variable is the amount of

[30]This is relevant since Chattopadhyay and Duflo (2004) find that women Sarpanches tend to invest more in certain types of infrastructure such that it captures the preferences of women electorate.

loan disbursed as a share of the total sanctioned loan, conditional on getting a loan. Since the disbursal rate is dependent on the rate of project completion, in doing so, I control for any differences which are specific to a particular type of infrastructure project.

The main coefficient of interest is β, which captures the effect of women's reservation on the outcome variable. Here, β compares the mean of Y for a given GP as reservation status changes over time. I am also interested in δ, which captures the differential impact of reservation for a woman from a disadvantaged caste.

For the estimate of β to be unbiased, it is necessary for the unreserved GPs to be a valid control group for the reserved GPs. This would be the case if the process of selection of GPs for reserving the Sarpanch position for women was actually random. To test whether this holds, I use Census data and compare the characteristics of the villages under reserved and unreserved GPs. The results for 2010 election cycle are presented in Table 3[31]. I use 2001 Census data to test for balance in the 2005 reservation process and 2011 Census data for 2010 and 2015 balance test. I find no statistically difference in the selected variables[32].

3.5 Results

This section presents the results from the baseline specification where I estimate the effect of reservation of Sarpanch position by comparing the outcome between the reserved and unreserved GPs exploiting the GP-level panel data structure, the

[31] The results for the other two cycles are in Tables A1 and A2 in the appendix.

[32] I find some difference in whether or not the village had a primary health center or a regular agricultural market. However, these differences are substantively small.

randomized assignment of women's reservation while controlling for caste reservation.

3.5.1 Baseline

Table 4 reports the panel estimates of the effect of reservation of the GP's Sarpanch position on the probability of the GP receiving an RDIF loan. The coefficient for the women's reservation is negative and significant in both columns (1) and (2). Looking at the dummy for receiving a loan under RDIF, this shows that GPs reserved for women Sarpanch are less likely to receive a loan by 1.7 pp after controlling for caste and other fixed effects. The coefficient for disadvantaged-caste reservation and the interaction term between caste and women dummy is negative suggesting a pattern of discrimination against Sarpanch from OBC, SC, ST castes, although it is not statistically significant.

Table 4 also presents the panel estimates of the effect of gender- and caste-based reservation on the loan disbursed as a share of the loan sanctioned[33], conditional on the GP receiving a loan. Column (2) show that even though women reserved GPs are less likely to receive a loan (as seen in Column (1)), the amount of loan disbursed as a share of the loan sanctioned is higher by 4.5 pp for women reserved GPs than unreserved GPs.

Further, the coefficient on caste dummy is also positive and significant. These results suggest that even though women Sarpanch might be less successful while applying for a loan, they might be better at meeting project progress targets, a

[33]There is no difference in the loan sanctioned as a share of the cost of the project between GPs that reserved for women or not. This is consistent with the fact that the amount of loan sanctioned as a share of the cost if fixed. For instance, projects for rural connectivity, social and agri-related sector are eligible for loans from 80 to 95 pp of project cost.

pre-requisite for loan disbursal[34]. However, compared to women GPs without caste reservation, loan disbursed for GPs reserved for women from disadvantaged castes is lower by 7.2 pp. This suggests that women from disadvantaged background face the double burden along both caste and gender lines.

3.5.2 Robustness

Full Sample: I also carry out the analysis on the full sample where I include all GPs that ever received a loan and include district fixed effects instead.

$$Y_{g,s,t} = \alpha_s + \tau_t + \eta_d + \beta R_{g,t} + \gamma C_{g,t} + \delta R_{g,t} * C_{g,t} + \epsilon_{g,s,t} \tag{3.2}$$

where $Y_{g,s,t}$ is the amount of loan disbursed as a rate of the loan sanctioned and η_d are district fixed effects. Here, district fixed effects account for the role played by district administration in RIDF implementation and any time-invariant district differences in RIDF performance, and administrative quality.

Table 5 reports the results from estimating the above regression on the full sample which is an unbalanced panel. The results for the entire sample in column (1) similar to the results from a balanced panel in Column (2) in Table 4. GPs reserved for woman Sarpanch have a higher loan disbursal rate by 1.7 pp than unreserved GPs. The coefficient for caste dummy is also positive and significant although the size of both the coefficients is smaller than before. However, the interaction between women and caste dummy is no longer significant. The results are robust to the use block level fixed effects instead in the analysis.

[34]RIDF loans are disbursed on re-reimbursement basis i.e., after the expenditure on the project has been made

3.6 Mechanism

My results show that women Sarpanch headed GPs are less likely to receive a loan for infrastructure development under RIDF scheme. There are few plausible explanations for such a finding. Women Sarpanch may be worse at lobbying for development funds due to lack of access to professional networks or limited negotiation skills or prejudiced bureaucrats.

3.6.1 Sarpanch Characteristics

I modify my preferred specification to include covariates for Sarpanch characteristics for the 2010 GP term. This controls the role of difference in observable traits other than Sarpanch gender in driving the difference in RIDF outcomes between reserved and unreserved GPs. The main coefficient β in this case is estimated by the following specification:

$$Y_{g,s,t} = \alpha_s + \theta_d + \beta R_{g,t} + \gamma C_{g,t} + \delta R_{g,t} * C_{g,t} + \lambda X_{g,t} + \epsilon_{g,s,t} \tag{3.3}$$

where t = 2010 and $X_{g,t}$ contains covariates on age, education, and occupation where Sarpanch age is measured in the number of years, education is a categorical variables which is classified as below primary schooling including illiterate, between primary and middle, between middle and senior secondary, and college and above. Finally, I include dummy variable for whether the Sarpanch is not-employed (this includes both those who are unemployed along with housewives, students, pensioners), and a dummy variable if the Sarpanch is engaged in the agriculture sector. Table 6 presents the summary statistics on covariates created from data on Sarpanch characteristics during the 2010 Rajasthan GP elections. We see that a Sarpanch is on average middle-aged, with up to middle school level of education and largely employed in agriculture.

Table 7 presents the results for the year 2010 without Sarpanch controls in Columns (1) and (3) and with controls in Columns (2) and (4). I find that including controls leaves the results unaffected both in terms of coefficient sign and magnitude[35]. This rules out the role of these easily observable traits in the determining the differential access to RIDF funds by women Sarpanch GPs.

3.6.2 Distance to District

Lobbying for development funds often requires regular trips to be made to the district authorities. Male Sarpanch can travel more out of their villages to meet district officials and other functionaries. Unlike men, women Sarpanch might not be able to spend long hours away from home due socio-economic constraints on their mobility[36]. If that is that case, one would expect that the negative impact on the probability of getting a loan increases with distance between the GP and district headquarters. This can be tested for by looking at the heterogeneity of the effect of reservation for women on RIDF outcomes with distance to the district headquarter.

I test for the effect of constraints on women's mobility on differential outcomes by running the following village-level regression:

[35] The coefficient on women reservation dummy for the dummy for whether the GP received a loan or not is negative and similar to the results based on the large sample but it is no longer significant.

[36] There is anecdotal evidence that women Sarpanch faced pressure from their families, and slander from neighbors for staying out late for work. Further, traveling involved loss of daily earnings which is not adequately compensated for by the Sarpanch salary or honorarium.

$$Y_{v,g,s,t} = \alpha_s + \tau_t + \theta_g + \beta R_{g,t} + \gamma C_{g,t} + \delta R_{g,t} * C_{g,t} + \mu D_{v,g} * R_{g,t} + \epsilon_{v,g,s,t} \quad (3.4)$$

where $D_{v,g}$ is a dummy variable which takes the value 1 if the distance of village v in GP g from its respective district headquarter is less than 20km and 0 otherwise[37].

Table 8 presents the heterogeneity of the effect of a woman Sarpanch with the distance to district HQ as captured by the coefficient on the interaction between the women reservation dummy and the dummy for village "close" to the district HQ. This coefficient is positive and significant for the outcome variable denoting that the GP received an RIDF loan. This shows that a village in a GP reserved for a woman Sarpanch that is within 20km of the district HQ has a 3 percent higher likelihood of receiving a loan than the GP village that is located farther than 20 km. This coefficient is not significant when looking at the rate of loan disbursal which is consistent with the process of loan disbursal as the sanctioned amount is deposited at the commercial bank near the GP. The results for the other variables remain the same in sign and go up in magnitude along with the model's R-sq compared to the results in Table 4 without distance control.

3.6.3 Bias

Women Sarpanch may be discriminated against by the male-dominated district and block authorities who exercise considerable power in the approval and sanction of these loans. One way to test this hypothesis is to compare the results found for

[37] 20km is roughly the 10th percentile of the distribution of village distance to district HQ in Rajasthan.

Rajasthan, a highly patriarchal society, with results estimated for a state like Kerala which does significantly better on indicators of women's education, health and social status.

I obtained the GP Sarpanch reservation data for Kerala for four GP terms: 2000 to 2015 from the State Election Commission and translated them from the local language, Malayalam, to English. RIDF loan data for the state for the corresponding years is publicly available. Combining data from these two sources, I then re-estimate my baseline equation for the state of Kerala. These results are presented in Table 9. Since the sample size of GPs that received a loan and could be identified based on the loans data is too small, I restrict the analysis to the probability of receiving the loan. I also include the results for the specification with interaction between the reservation dummy and distance dummy variable. Neither set of results are significant. The main coefficient on women reservation dummy is small and insignificant.

3.7 Discussion

Empirical evidence on the performance of women leaders attributes the difference in outcomes to factors such as difference in leadership style, preferences (Chattopadhyay and Duflo, 2004; Ban and Rao, 2008), inexperience (Afridi et al., 2017) or difference in perceptions of and attitudes towards women Sarpanch (Duflo et al., 2004). However, the ability to raise funds is an important fiscal lever to influence welfare outcomes which has received inadequate attention[38].

[38] This can be attributed to a large extent to the (1) limited ability of GPs to raise their own revenue and reliance on state and federal transfers, and (2) limited administrative data on GP finances. Further, some studies that explored the financial management at the GP level have found little evidence of a significant difference in the GP-level expenditures or own revenues collected for

However, there is research in other context, for instance, Asiedu et al. (2013) find that female-owned firms were more credit constrained than male-owned firms in Sub-Saharan Africa, that provide a rationale for investigating this channel in the political context. One such study is by Bardhan et al. (2010) where the authors find that villages in West Bengal with a reserved Sarpanch position raised lower local revenues and received fewer funds from the district authorities under employment programs. At the same time, these villages were able to secure more credit from the banks under another program by persistently following up on villagers' applications. Similarly, Afridi et al. (2017) find greater irregularities in the implementation of employment program in women reserved GPs which they attribute to the inexperience of women Sarpanches. However, these gaps close as women leader gain greater experience implying that women leader might be better managers. The results found in my paper are consistent with these findings. In this paper, I am able to look at the two aspects of obtaining a loan and ensuring loan disbursal within the same program, with greater bureaucratic discretion, and offering new evidence that builds on this growing literature.

Looking at the plausible mechanism driving these results, I find that lower distance to the district HQ results raises the probability that the GP with a woman Sarpanch received a loan. Here, greater distance to district administration implies greater travel time and costs thereby limiting the ability of women Sarpanch to access funds either directly by accessing information about government schemes and funding opportunities or indirectly by building professional networks with officials to lobby for greater resources. The ''cost of distance" and barriers to women's travel due

reserved versus unreserved GPs, for instance, Rajaraman and Gupta (2008) to gendered societal norms around visibility, mobility, and issues of safety are well documented in Borker (2024); Muralidharan and Prakash (2017); Asher et al. (2018). Further, the disadvantages of not being able to access powerful, male-dominated professional networks is well-studied in the literature on women leaders (Athey et al., 2000; Rosenthal and Strange, 2012). This is valid and worse in the Indian political context (Gajwani and Zhang, 2015). (Purohit, 2024) findings show that mid-level bureaucrats perceive women Sarpanch to have fewer networks and are likely to reject their aid requests at greater rates than men. The author also finds that this negative perception doesn't extend to men from disadvantaged caste which is consistent with my results as the coefficient on the caste dummy is positive and significant for the rate of loan disbursal (Column (2) in Table 5).

An explanation offered by the literature on women leaders which could explain these results include difference in Sarpanch traits such as risk aversion (eg., Levi et al., 2010) and unobserved political skills (Ferreira and Gyourko, 2011). While I am not able to measure risk aversion or experience directly, I test for this hypothesis by controlling for observable characteristics such as Sarpanch age, education, and occupation and find that my results are similar to when I do not include those covariates. Another explanation would be that, unlike (Purohit, 2024), discriminatory behavior by officials is not based on strategic concerns about women Sarpanch's mobilization ability but on gender stereotypes or a response to defiance of social norms and a perceived challenge to their authority (Gangadharan et al., 2016). I find some support when I test whether this theory holds in a more ''liberal" social context of the state of Kerala as the original set of results no longer hold.

3.8 Conclusion

Political reservation for women is an extremely popular policy tool in developing countries for addressing gender gaps in policy decision making and its intended outcomes.

In this paper, I examine if, despite reservation, there persists gender disparity in access to development funds under RIDF. I find that women leaders in reserved GPs in Rajasthan have a lower likelihood of receiving an RIDF loan, although conditional on receiving a loan, they have a high rate of loan disbursal. The negative effect is even greater for women Sarpanch in GPs reserved for disadvantaged castes.

I provide evidence that suggests that these results could be driven by (1) women Sarpanches' inability to lobby for funds by travelling to the district HQ as frequently as their male counterparts, and (2) social prejudice against women. I test for the role of Sarpanch characteristics and do not find support for the hypothesis as the results remain unaffected when I include covariates for observables such as age and education.

The main implication of our results is that while electoral quotas for women are effective at increasing participation but once in office, the performance of women leaders maybe hindered by socio-economic factors that deterred entry in the first place. Further, these results offer new evidence on the channel driving the difference in the previously studied outcomes such as provision of local goods and services. At the same time, there is scope for further exploration in this area. For instance, due the nature of RIDF data, it was only possible me to look at loans released under three sectors: health, education and agriculture centers. Given the evidence on the role of

Sarpanch preferences, it would be worthwhile to look into demand for funds under other sectors such as water and roads. Further, women Sarpanch may be less likely to demand loans due to lack of information about the scheme. However, it would be difficult to test this hypothesis without information on the request for loans made by respective GP Sarpanches and its rate of approval. Another explanation could be that women Sarpanch have differential preferences and demanded fewer loans under RIDF.

Tables

	N	Mean	Std Dev	Min	Max
Education Infrastructure					
Cost of Project	3482	19.36	15.99	0.41	84.98
Loan Sanctioned	3482	16.10	13.30	0.35	72.23
Loan Disbursed (%)	3482	0.57	0.33	0	1
KSK-VKC-LRIC					
Cost of Project	2464	9.87	0.74	9	10.50
Loan Sanctioned	2464	9.38	0.70	8.55	9.98
Loan Disbursed (%)	2464	0.71	0.32	0.02	1
Public Health Institutions					
Cost of Project	1893	75.96	96.21	27	525
Loan Sanctioned	1893	64.49	81.63	22.95	444.10
Loan Disbursed (%)	1893	0.58	0.38	0	1

Notes: The table presents information on the RIDF loans sanctioned under the three sectors, namely-education, agriculture and allied, and health, for the GP sample used in the study. The time period covers GP terms 2005, 2010, and 2015. The cost of project and loan sanctioned figures are in rupees lakhs and loan disbursed is a share of the loan sanctioned.

Table 1: Summary Statistics

	2005		2010		2015	
	No.	%	No.	%	No.	%
Unreserved	269 (6102)	4.41	463 (4806)	9.63	511 (4558)	11.21
Reserved	3068 (3070)	99.93	4359 (4359)	100	4724 (4724)	100
Total	3337 (9172)	36.38	4822 (9165)	52.61	5235 (9282)	56.40

Notes: The table presents the number and the fraction of women Sarpanch in reserved and unreserved GPs during the 2005, 2010, and 2015 GP terms. The total number of GPs in each category is given in parenthesis. The Government of Rajasthan increased the rate of reservation for women in Panchayats from 33% to 50% pursuant to 'The Rajasthan Panchayati Raj (Second Amendment) Act, 2008'.

Table 2: Fraction of Women Sarpanch in Reserved and Unreserved GPs

	(1) Unreserved Mean/(SE)	(2) Reserved Mean/(SE)	(1)-(2) Pairwise t-test Mean difference
Govt Primary School	0.725	0.726	-0.001
	(0.004)	(0.004)	
Govt Middle School	0.444	0.440	0.004
	(0.004)	(0.004)	
Govt Secondary School	0.291	0.294	-0.003
	(0.004)	(0.004)	
Govt Senior Secondary School	0.098	0.098	0.000
	(0.002)	(0.002)	
Public Health Center	0.361	0.369	-0.007
	(0.004)	(0.004)	
Area Irrigated (%)	0.419	0.424	-0.005
	(0.003)	(0.003)	
Mandis/Regular Market	0.201	0.204	-0.003
	(0.003)	(0.003)	
Commercial Bank	0.140	0.139	0.001
	(0.003)	(0.003)	
Cooperative Bank	0.146	0.148	-0.001
	(0.003)	(0.003)	
All Weather Road	0.293	0.293	0.000
	(0.004)	(0.004)	
F-test of joint significance			1.316
F-test, number of observations			30583

Notes: The table presents the village infrastructure in reserved and unreserved GPs during the 2010 GP term using 2011 Census data. The total number of observation for Column (1) is 16803, in Column (2) is 14500, and in Column (3) is 30583. The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. 82% of the GPs were successfully matched to their respective villages and linked to the 2011 Census data. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Balance Test

	Loan (0/1)	Disbursal (share)
	(1)	(2)
Women Res.	-0.017*	0.045**
	[0.010]	[0.019]
Caste Res.	-0.0005	0.040**
	[0.008]	[0.018]
Women Res. × Caste Res.	0.008	-0.072**
	[0.013]	[0.031]
Sector FEs	No	Yes
GP FEs	Yes	Yes
Term FEs	Yes	Yes
Control mean	0.219	0.626
Observations	27,363	2,374
R-sq	0.356	0.747

Notes: Outcome variable in column (1) is a dummy for whether a GP received a loan, in Columns (2) is amount of loan disbursed, as a share of the total amount of loan sanctioned for the GP in a given sector conditional on receiving a loan. Unit of observation is at the GP level. Women Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for women and 0 if it is unreserved. Caste Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for a person belonging to disadvantaged caste i.e. SC/ST/OBC and 0 if it is unreserved. Regressions include GP fixed effects, term, and sector (health, education, and agri-allied) fixed effects. Standard errors in brackets, clustered at block level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of Reservation for Female Sarpanch on RIDF Loan

	Disbursal (share) (1)
Women Res.	0.017*
	[0.009]
Caste Res.	0.019**
	[0.008]
Women Res. × Caste Res.	-0.019
	[0.012]
Sector FEs	Yes
District FEs	Yes
Term FEs	Yes
Control mean	0.626
Observations	6,190
R-sq	0.520

Notes: Outcome variable in column (1) is amount of loan disbursed, as a share of the total amount of loan sanctioned for the GP in a given sector. Unit of observation is at the GP level. Women Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for women and 0 if it is unreserved. Caste Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for a person belonging to disadvantaged caste i.e. SC/ST/OBC and 0 if it is unreserved. Regressions include district GP term, fixed effects, and sector (health, education, and agri-allied) fixed effects. Standard errors in brackets, clustered at block level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of Sarpanch Reservation Effect on Loan Disbursal: District FEs

	Mean
Age (years)	45.36
Education	
(%) Less than primary	5.39
(%) Primary to Middle	68.99
(%) Middle to High	16.41
(%) College & above	9.20
Occupation	
(%) Agri.	61.31
(%) Not-employed	33.13

Notes: The table presents statistics based on the data on Sarpanch characteristics obtained from Das et al., (2023). Agri. indicates if the Sarpanch is engaged in the agriculture as a farmer, laborer or in livestock cultivation. Not-employed includes unemployed as well as housewives, students, retired or pensioners.

Table 6: Summary Statistics: Sarpanch Characteristics

	Loan (0/1)		Disbursal (share)	
	(1)	(2)	(3)	(4)
Women Res.	-0.019	-0.018	0.051***	0.052**
	[0.017]	[0.021]	[0.019]	[0.023]
Caste Res.	0.005	0.008	0.038**	0.038**
	[0.015]	[0.015]	[0.019]	[0.019]
Women Res. × Caste Res.	0.017	0.016	-0.064**	-0.063**
	[0.022]	[0.023]	[0.025]	[0.025]
Sector FEs	No	No	Yes	Yes
District FEs	Yes	Yes	Yes	Yes
Sarpanch Controls	No	Yes	No	Yes
Dep var mean	0.308	0.308	0.719	0.719
Observations	6,643	6,643	2,005	2,005
R-sq	0.055	0.057	0.129	0.130

Notes: Outcome variable in column (1) and (2) is a dummy for whether a GP received a loan, in Columns (3) and (4) is amount of loan disbursed, as a share of the total amount of loan sanctioned for the GP in a given sector. Unit of observation is at the GP level, and pertains to 2010 GP Term. Women Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for women and 0 if it is unreserved. Caste Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for a person belonging to disadvantaged caste i.e. SC/ST/OBC and 0 if it is unreserved. Regressions include district fixed effects, and sector (health, education, and agri-allied) fixed effects. Sarpanch controls include candidate age (in years), dummy variable for being employed, and for being engaged in the agriculture sector (as a farmer or a laborer), and a categorical variable for candidate education classified as less than primary, primary to middle, middle to high, and college or above. Standard errors in brackets, clustered at block level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effect of Reservation for Female Sarpanch on RIDF Loan: Sarpanch control

	Loan (0/1)	Disbursal (share)
	(1)	(2)
Women Res.	-0.027**	0.059**
	[0.012]	[0.026]
Women Res. × Dist_HQ ≤ 20km	0.030**	-0.011
	[0.015]	[0.020]
Caste Res.	-0.004	0.046**
	[0.011]	[0.023]
Women Res. × Caste Res.	0.008	-0.093**
	[0.015]	[0.038]
Sector FEs	No	Yes
GP FEs	Yes	Yes
Term FEs	Yes	Yes
Control mean	0.216	0.619
Observations	95,852	20,933
R-sq	0.368	0.910

Notes: Outcome variable in column (1) is a dummy for whether the GP received a loan, and in Column (2) is amount of loan disbursed, as a share of the total amount of loan sanctioned for a GP in a given sector. Unit of observation is at the GP-village level. Women Res.is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for women and 0 if it is unreserved. Caste Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for a person belonging to disadvantaged caste i.e. SC/ST/OBC and 0 if it is unreserved. Dist_HQ $\leq$ 20km is dummy variable that takes the value 1 if the distance between village and its district HQ is less than or equal to 20km and 0 otherwise. Standard errors in brackets, clustered at block level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Heterogeneity of Effect of Female Sarpanch with Distance

	Loan (0/1)	
	(1)	(2)
Women Res.	-0.001	-0.002
	[0.016]	[0.018]
Women Res. $\times$ Dist_HQ $\leq$ 10km		0.011
		[0.034]
Caste Res.	-0.040	-0.037
	[0.029]	[0.026]
Women Res. $\times$ Caste Res.	0.009	0.001
	[0.042]	[0.036]
GP FEs	Yes	Yes
Term FEs	Yes	Yes
Control mean	0.118	0.118
Observations	3,909	3,600
R-sq	0.339	0.330

Notes: The Outcome variable in column (1) is a dummy for whether a GP received a loan. Unit of observation is at the GP level and time period covers 2000, '05, '10, and '15 GP terms. Women Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for women and 0 if it is unreserved. Dist_HQ $\leq$ 10km is a dummy variable that takes the value 1 if the village distance to its district headquarter is less than or equal to 10km, which is the 10th pc of the distance distribution for villages in Kerala. Caste Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for a person belonging to disadvantaged caste i.e. SC/ST and 0 if it is unreserved. Regressions include GP fixed effects, and term fixed effects. Standard errors in brackets, clustered at block level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effect of Reservation for Female Sarpanch in Kerala

3.9 Appendix

3.9.1 Balance Test

	(1) Unreserved Mean/(SE)	(2) Reserved Mean/(SE)	(1)-(2) Pairwise t-test Mean difference
Govt Primary School	0.858	0.859	-0.000
	(0.003)	(0.004)	
Govt Middle School	0.368	0.370	-0.002
	(0.004)	(0.005)	
Govt Senior Secondary School	0.110	0.108	0.002
	(0.002)	(0.003)	
Primary Health Center	0.048	0.042	0.005**
	(0.002)	(0.002)	
Commercial Bank	0.052	0.050	0.002
	(0.002)	(0.002)	
Cooperative Bank	0.027	0.027	0.000
	(0.001)	(0.002)	
Approach Road-Paved	0.553	0.548	0.005
	(0.004)	(0.005)	
F-test of joint significance (F-stat)			0.825
F-test, number of observations			27296

Notes: The table presents the village infrastructure in reserved and unreserved GPs during the 2005 GP term using 2001 Census data. The total number of observation for Column (1) is 18027, in Column (2) is 9269, and in Column (3) is 27296. The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. 82% of the GPs were successfully matched to their respective villages and linked to the 2011 Census data. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Balance Test

3.9.2 Robustness

	(1) Unreserved Mean/(SE)	(2) Reserved Mean/(SE)	(1)-(2) Pairwise t-test Mean difference
Govt Primary School	0.733	0.732	0.001
	(0.003)	(0.004)	
Govt Middle School	0.439	0.447	-0.007
	(0.004)	(0.004)	
Govt Secondary School	0.286	0.286	-0.000
	(0.003)	(0.004)	
Govt Senior Secondary School	0.096	0.095	0.001
	(0.002)	(0.002)	
Public Health Center	0.367	0.364	0.003
	(0.004)	(0.004)	
Mandis/Regular Market	0.200	0.208	-0.008*
	(0.003)	(0.003)	
Commercial Bank	0.137	0.141	-0.004
	(0.003)	(0.003)	
Cooperative Bank	0.144	0.148	-0.004
	(0.003)	(0.003)	
All Weather Road	0.295	0.300	-0.005
	(0.004)	(0.004)	
F-test of joint significance (F-stat)			1.519
F-test, number of observations			32669

Notes: The table presents the village infrastructure in reserved and unreserved GPs during the 2015 GP term using 2011 Census data. The total number of observation for Column (1) is 16804, in Column (2) is 15865, and in Column (3) is 32669. The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. 82% of the GPs were successfully matched to their respective villages and linked to the 2011 Census data. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Balance Test

	Loan (0/1)	Disbursal (share)
	(1)	(2)
Women Res.	-0.014**	0.010
	[0.006]	[0.012]
Sector FEs	No	Yes
GP FEs	Yes	Yes
Term FEs	Yes	Yes
Control mean	0.219	0.626
Observations	27,363	2,374
R-sq	0.356	0.746

Notes: Outcome variable in column (1) is a dummy for whether a GP received a loan, in Column (2) is amount of loan disbursed, as a share of the total amount of loan sanctioned for the GP in a given sector conditional on receiving a loan. Unit of observation is at the GP level. Women Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for women and 0 if it is unreserved. Regressions include GP fixed effects, term, and sector (health, education, and agri-allied) fixed effects. Standard errors in brackets, clustered at block level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect of Reservation for Female Sarpanch on RIDF Loan

	Loan (0/1)		Disbursal (share)	
	(1)	(2)	(3)	(4)
Women Res.	-0.020*	-0.022**	0.057***	0.064***
	[0.010]	[0.011]	[0.020]	[0.021]
Women Res. × dist_HQ	0.057*	0.024	-0.014	-0.049
	[0.034]	[0.018]	[0.088]	[0.031]
Caste Res.	-0.004	-0.004	0.044**	0.043**
	[0.009]	[0.009]	[0.019]	[0.019]
Women Res. × Caste Res.	0.006	0.006	-0.092***	-0.090***
	[0.014]	[0.014]	[0.032]	[0.032]
Distance	10km	20km	10km	20km
Sector FEs	No	No	Yes	Yes
GP FEs	Yes	Yes	Yes	Yes
Term FEs	Yes	Yes	Yes	Yes
Control mean	0.219	0.219	0.626	0.626
Observations	23,738	23,738	2,112	2,112
R-sq	0.358	0.358	0.746	0.746

Notes: Outcome variable in column (1) is a dummy for whether the GP received a loan, and in Column (2) is amount of loan disbursed, as a share of the total amount of loan sanctioned for a GP in a given sector conditional on receiving a loan. Unit of observation is at the GP level. Women Res.is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for women and 0 if it is unreserved. Caste Res. is a dummy that takes the value 1 when a GP's Sarpanch position is reserved for a person belonging to disadvantaged caste i.e. SC/ST/OBC and 0 if it is unreserved. Dist_HQ is dummy variable that takes the value 1 if the distance between village and its district HQ is less than or equal to 10km in Columns (1) and (3), and 20km in Columns (2) and (4) and 0 otherwise. Standard errors in brackets, clustered at block level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tabl A4: Heterogeneity of Effect of Female Sarpanch with Distance: GP Level

4

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