Electricity and the Environment

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Thesis submitted to the Indian statistical Institute in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy

July, 2024

Acknowledgement

This PhD thesis marks the culmination of a long and transformative journey, and it would not have been possible without the support, guidance, and encouragement of numerous individuals and institutions. First and foremost, I express my deepest gratitude to my PhD supervisor, Professor E. Somanathan, whose expertise, patience, and unwavering support have been invaluable throughout this journey. His insightful feedback has shaped this research in countless ways. Thank you for understanding, appreciating, and giving shape to my ideas. I am deeply indebted to my family for their unconditional love and support. My mother and father, whose sacrifices and encouragement have always motivated me to pursue my dreams, and my sisters and brother, who have been my pillars of strength. I would like to extend my heartfelt thanks to my co-authors, Eshita Gupta and Marc Jeuland, for their collaboration and valuable contributions to my research. Their insights and dedication have significantly enriched this work. I am also grateful to the esteemed professors at ISI Delhi and beyond, whose guidance and mentorship have been instrumental in my academic journey. I thank Professor Abhiroop Mukhopadhyay, Professor Tridip Ray and Professor Nishith Prakash for their invaluable advice and support.

My sincere appreciation goes to the Indian Statistical Institute, Delhi, for providing a conducive research environment and the necessary financial support through stipends. The resources and facilities made available to me were crucial in the successful completion of my research. I extend my gratitude to the Environment for Development (EfD) for their research funding, to conduct high-quality research for Chapters 3 and 4 of my thesis. I extend my sincere thanks to the Centre for Research on the Economics of Climate, Food, Energy, and Environment (CECFEE) for providing a platform that enabled focused research on environmental issues. I would like to express my heartfelt thanks to my previous institutions—Sainik School Nalanda, Hansraj College, and Jawaharlal Nehru University—for their pivotal roles in shaping both my academic and personal development.

I am fortunate to have had the support of my friends and colleagues at ISI Delhi, whose camaraderie and encouragement have made this journey enjoyable and fulfilling. Harshika, Mayank, Ojasvita, Komal, Hemant, Aditya, Ankit, Priyanka, Agnij, Pankaj, Subhadeep,

and Vrinda, your friendship and support—mentally, physically, and emotionally—have been indispensable. Your friendship and unwavering support have meant a great deal to me, providing me with the strength and motivation to persevere. A special mention goes to football and badminton at ISI Delhi, which have been constant sources of endorphins during tough as well as good times.

In closing, I acknowledge everyone who has been a part of this journey, whether mentioned here by name or not. Your contributions, big and small, have been vital to the completion of this thesis. Thank you all for being a part of this journey with me.

Praveen Kumar.

To my parents

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Chapter 1

Introduction

This thesis comprises three chapters that explore the interaction between electricity and the environment. Electrification is a boon to society, widely discussed in literature for its influence on numerous outcomes. Its impact on the environment can be positive or negative, depending on how it is used. This thesis examines two specific aspects of electricity: first, the effect of power policy on groundwater, and second, how electrification can be accompanied with use of electric cooking to help reduce environmental pollutants in both institutional and household settings. In the second chapter, titled 'Removing Rationing: Power Consumption and Groundwater Monitoring in South India', coauthored with Eshita Gupta and E. Somanathan, we investigate the effects and implications of power policies on groundwater and power consumption. The third chapter, titled 'Effects of a Transition from LPG to Induction cookstoves in Kerala Anganwadis, India' coauthored with Eshita Gupta, E. Somanathan, and Fizza, examines how transitioning from LPG to induction cookstoves can reduce costs and total cooking time. It also looks at the adoption of new cooking technology in an institutional Anganwadi framework, even when the upfront cost of induction cookstoves is subsidized. The fourth chapter, titled 'Electricity as a Clean Cooking Option: What Can We Learn from Cross-Country Comparisons?', coauthored with Eshita Gupta, E. Somanathan, and Marc Jeuland, explores the enablers and barriers to the adoption of electric cooking in various countries and contexts. Each chapter is described briefly below.

1.1 Removing Rationing: Power Consumption and Groundwater Monitoring in South India

This chapter studies the impact of removing power rationing on groundwater and power consumption. Groundwater, being available on demand, is a more reliable source for irrigation. The number of tubewells has increased rapidly since 1962, making them the primary irrigation source in India. The Central Ground Water Board reports that approximately 85% of the rural population's drinking water needs are met by groundwater. Between 1970 and 1995, the rapid expansion of groundwater irrigation induced an agrarian boom but also led to chronic resource depletion and quality deterioration (Shah et al., 2003). The depletion of this vital resource has raised serious concerns (Ryan and Sudarshan, 2022; Sekhri, 2012-13).

Power supply policy is a key driver of groundwater depletion. In nearly all Indian states, agricultural power supply is unmetered, with farmers paying a monthly charge based on tubewell capacity, resulting in a zero marginal cost for additional power use. This incentivizes excessive pumping, leading to rapid groundwater depletion (Sidhu, Kandlikar, and Ramankutty, 2020). Telangana, a state in southern India is the only state in India providing uninterrupted free power to farmers. The primary aim of this policy was to enhance electricity availability for pump sets, thus increasing water accessibility for irrigation. However, this could potentially lead to groundwater depletion, especially in semi-arid regions like Telangana during periods of deficient rainfall.

This study investigates the impact of Telangana's unrestricted power policy on groundwater resources. This research makes both substantive and methodological contributions. Substantively, the effect of removing power rationing on power consumption and groundwater levels are examined using data from monitoring wells in Telangana and neighboring states before and after the policy change. Methodologically, a geographical difference-in-differences approach is applied.

District-level monthly panel on agricultural power consumption shows a 51% increase in Telangana's agricultural power consumption following the removal of rationing. However, the geographical difference-in-differences analysis does not indicate a corresponding increase

in groundwater depth in monitoring wells compared to neighboring states over the two years following the policy change. This suggests that the monitoring wells may not capture the groundwater depth data from farmer wells accurately, especially in the heterogeneous hard-rock aquifers of Telangana. These findings imply that the design of monitoring well placement needs reconsideration for accurate groundwater assessment in hard-rock aquifers.

1.2 Effects of a Transition from LPG to Induction cookstoves in Kerala Anganwadis, India

Half of Indian households continue to rely on firewood for cooking, with only 5% using electric cooking appliances despite 100% electrification (Agrawal et al., 2021). Traditional cookstoves produce harmful pollutants, causing severe health issues such as stroke, heart disease, and lung cancer (IEA, 2023; Balmes, 2019; Schraufnagel et al., 2019). Women and children are disproportionately affected due to their roles in cooking and firewood collection (Maes and Verbist, 2012; Yu et al., 2021).

This chapter examines the changes in LPG fuel consumption, total cooking time, and adoption patterns following the implementation of a subsidized induction cookstove program. Electric cooking, particularly induction cookstoves, offers higher efficiency and reduced indoor air pollution compared to LPG and traditional stoves (Shen et al., 2018; Gould et al., 2023). Induction cookstoves can significantly lower PM2.5 levels in kitchens and reduce emissions (Arora et al., 2020; Somanathan et al., 2022). Studies from Ecuador and other countries show that transitioning to electric cooking reduces greenhouse gas emissions and improves health outcomes (Gould et al., 2023; Irsyad et al., 2022). However, there is limited research on the determinants of electric cooking adoption and its variable costs in India. This study examines these aspects in an institutional setup, focusing on the adoption and impact of induction cookstoves in public child care centers (Anganwadis) in Kerala.

A difference-in-differences method is used to analyze administrative and survey data, assessing changes in LPG consumption and cooking time. The findings indicate a 10%

reduction in LPG consumption post-intervention. We find a corresponding increasse in electricity consumption using administrative data. Our findings show that Anganwadis are saving roughly 300 INR per month on average, by partially adopting induction cookstoves. Although the decrease in cooking time was not statistically significant, users reported that induction cookstoves were convenient, cheaper, safe, and tidy. Non-adoption was mainly due to inadequate electricity infrastructure in Anganwadis. This research contributes to understanding the benefits and barriers of electric cooking adoption in an institutional framework, providing insights for scaling clean cooking solutions.

1.3 Electricity as a Clean Cooking Option: What Can We Learn from Cross-Country Comparisons?

This chapter examines the factors affecting the adoption of electric cooking in various contexts. Air pollution is a significant global health concern (Cohen et al., 2017; Lelieveld et al., 2020). Cleaner and more efficient cooking solutions are needed. Electric cooking is a viable alternative, offering health and environmental benefits and saving time, especially where fuel collection is labor-intensive (Krishnapriya et al., 2021).

Electric cookstoves, particularly induction cookstoves, are more efficient, reaching up to 90% efficiency compared to LPG's 45-60% (Ayub et al., 2021; Zhang et al., 2000; Sadhu et al., 2010). Electric cooking is also economically advantageous to households (ESMAP, 2020; Scott and Leach, 2023; Roy, 2024; Jain, Choudhury, and Ganesan, 2015). Transitioning to electric cooking powered by renewables can significantly reduce total carbon footprints, offering both private and social benefits. Specific to electric cooking, Somanathan et al. (2022) showed that electricity availability increases induction cookstove use, reducing air pollution in India. Alem, Hassen, and Köhlin (2014) identified electricity and firewood prices and access to credit as key determinants in urban Ethiopia. Paudel, Sharifi, and Khan (2023) found that monthly expenses and electricity supply influence induction cooking choices. Rubinstein et al. (2022) identified costs, energy reliability, safety concerns, reluctance to replace traditional fuels, and policy commitment as factors influencing electric pressure cooker adoption in urban Cameroon.

A systematic studies on determinants of electric cooking adoption in low and lower-middle-income countries are lacking, especially on policy-amenable factors like reliability. This chapter fills this gap by combining econometric and qualitative analyses to explore factors influencing electric cooking adoption, such as electricity reliability, pricing, gender and other socioeconomic factors. Using India Residential Energy Survey as well as World Bank's Multi Tier Framework data for Nepal and Myanmar, findings suggest that these factors vary by country-specific contexts. Qualitative analysis provides additional insights, identifying barriers like induction cookstove failures, lack of electric cookstove repair shops, electricity quality, seasonal electricity variations and household electricity infrastructure. Conversely, cooking speed and fuel availability enable adoption. Understanding these factors is crucial for designing effective policies to promote cleaner cooking solutions and improve health and environmental outcomes.

Each chapter is described in detail in the subsequent chapters.

Chapter 2

Removing Rationing: Power Consumption and Groundwater Monitoring in South India

2.1 Introduction

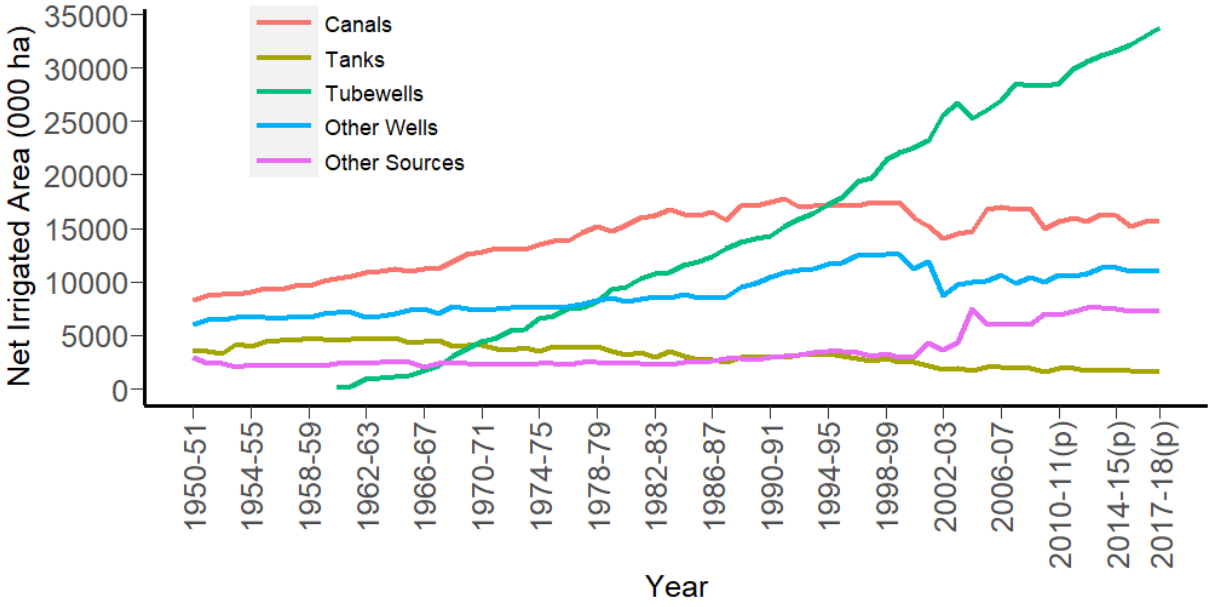
Indian agriculture is heavily dependent on groundwater for irrigation, and its depletion is a serious concern (Ryan and Sudarshan, 2022; Sekhri, 2012-13). The number of tubewells has grown rapidly since 1962 and they are now the primary source of irrigation in India (Figure 2.1). Groundwater accounted for 65% of the net irrigated area in 2019-20. According to the Central Ground Water Board, approximately 85% of the rural population's drinking water requirements are fulfilled by groundwater sources. Over the period from 1970 to 1995, the rapid growth of groundwater irrigation in India served as the primary catalyst for the agrarian boom. However, this period also brought about a chronic issue of resource depletion and quality deterioration (Shah et al., 2003). The depletion of nonrenewable aquifers is occurring at an increasing rate in India (Sekhri, 2012-13).

Power supply policy is a major driver of groundwater depletion. Agricultural power supply is unmetered in nearly all Indian states. Farmers pay a monthly charge based on the capacity of tubewells, and the marginal cost of using extra power is zero, as in Telangana, the state studied in this paper.[1] A zero marginal cost of power faced by farmers incentivises pumping beyond the efficient level, resulting in rapid depletion of groundwater (Sidhu,

[1]There are two main reasons why distribution companies and farmers might be disincentivised from installing power meters at the point of consumption. Firstly, since the state subsidises agricultural power consumption, distribution companies tend to overestimate the amount of power consumed by farmers (in the absence of metering, it is impossible to determine the exact agricultural power consumption), while underestimating their own distribution loss, resulting in higher subsidy claims from the government (Dabadge et al., 2018b). Secondly, farmers are apprehensive that if power meters are installed, state governments may terminate power subsidies. Due to this concern, even metering at the transformer level is being protested in Andhra Pradesh, a neighboring state of Telangana (TheNewsMinute, 2020).

Kandlikar, and Ramankutty, 2020), so state distribution companies ration the hours of power supplied per day in most states. Using a survey in the state of Rajasthan, Ryan and Sudarshan (2022) found that rationing results in farmers pumping more than the efficient quantity of groundwater on average unless a very high discount rate is assumed in valuing the depletion externality. There is a tendency to over-irrigate major water-intensive crops like rice (Sarkar, 2012). This tendency to over-irrigate is reinforced by discontinuous power supply (rationed number of hours per day) and unannounced interruptions, causing farmers to pump as much water as possible whenever power is available (Kumar, Scott, and Singh, 2011). Our paper examines the impact of removing the rationing of free power for agriculture on groundwater and agricultural power consumption. To the best of our knowledge, this is the first study to examine the consequences of augmenting daily hours of power supply on the groundwater resources.

Figure 2.1. Sources of irrigation in India since 1950.



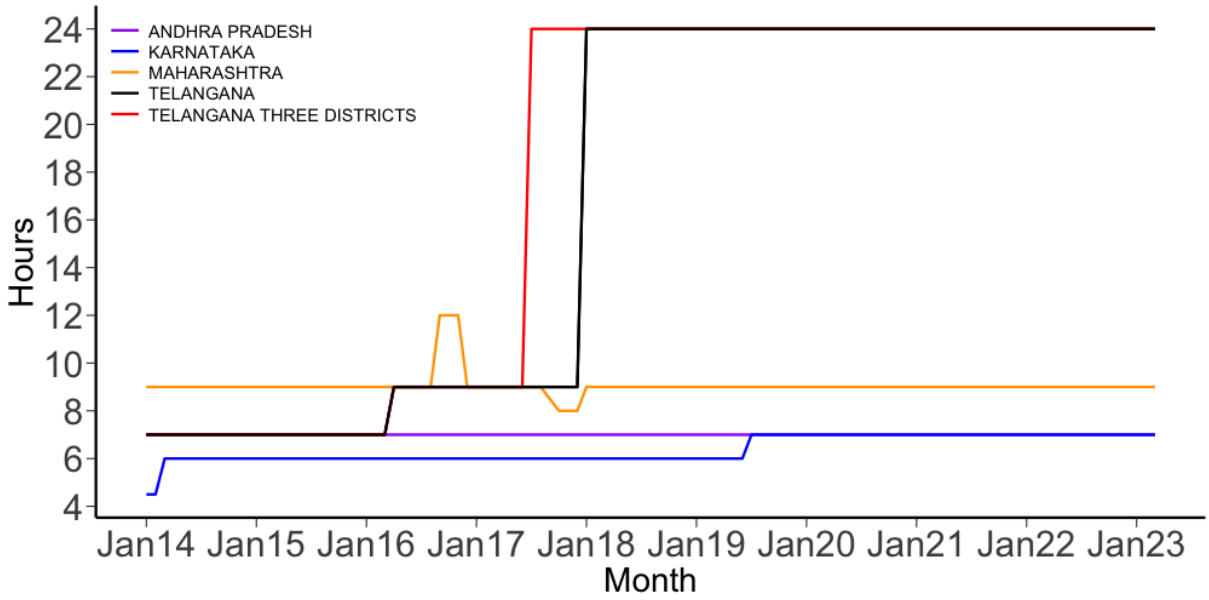
Notes: P stands for provisional data.

Source: Based on data from Directorate of Economics & Statistics, Ministry of Agriculture, Government of India.

The state of Telangana in south India initiated a program offering 24/7 free electricity to farmers starting January 1, 2018. Prior to the full-scale launch, a pilot version of this program was rolled out in mid-July 2017 across three districts: Nalgonda, Karimnagar, and Medak (CEA, March-2018; TSERC, 2018). Telangana stands out as the sole state in

India that offers free power supply to farmers around the clock. Figure 2.2 shows that there has been a huge increase in the daily hours of power supply, whereas neighboring states have not undergone any major changes in this regard.[2] The stated reason behind providing free 24x7 power supply to farmers in Telangana was to enhance the availability of electricity for pump sets, thereby increasing water accessibility for irrigation purposes (TheNewsMinute, 2018). Of course, the policy could result in depletion of groundwater reserves in semi-arid regions like Telangana, where well density has increased from 5 wells/km^2 in 1985-86 to 27 wells/km^2 in 2019-20, reducing the irrigated area per well from 4-6 hectares to less than 1 hectare (*Dynamic Groundwater Resources of Telangana State* 2022).

Figure 2.2. Daily average hours of agricultural power supply.



Source: Based on multiple monthly executive summary reports by Central Electricity Authority

Previous studies by Duflo and Pande (2007) and Sekhri (2014) have shown that water availability is associated with an increase in production and a decline in poverty. We look at how this water availability itself is affected by removing rationing of a critical input for extraction, thus contributing to the empirical literature on the economic drivers of depletion. Sekhri (2012-13) found that the policy that delayed transplanting of rice

[2]Map for boundary states and districts, including the pilot policy districts, are shown in Appendix Figure 2.11.

in order to reduce water extraction, perversely resulted in increased use of groundwater in Punjab and Haryana. Chatterjee, Lamba, and Zaveri (2024) examined the effect of procurement incentives for water-intensive crops and found that there is a shift towards water-intensive crop cultivation, and it has a significant negative impact on groundwater. Sidhu, Kandlikar, and Ramankutty (2020) in a review of multiple case study papers on flat and metered tariff show that flat tariffs result in more equitable groundwater distribution but offer no incentive for water conservation, whereas metered tariffs encourage judicious consumption but are costly to manage and disadvantageous to low-income farmers who often have to buy water from wealthier well owners. Gupta (2023) found that the shift from flat tariff to zero tariff in Punjab has resulted in an increase in groundwater depth by 22 percent. Badiani and Jessoe (2018) using panel data from 370 districts showed that electricity subsidies have increased groundwater extraction in India.

Our study differs from previous research in that we examine the impact of the removal of power supply rationing, specifically the implementation of twenty-four-hour power supply, on groundwater resources in a hard rock aquifer dominated region. Hard rock regions occupy over two-thirds of the surface area in India and approximately 20 percent of the land surface in the world (Singhal, 2008). Empirical studies using point-level microdata for a large area have been limited to regions that are dominated by alluvial aquifers. Therefore, our study fills an important gap in the literature by estimating the effects of unrestricted power supply on groundwater in hard rock aquifer regions. Aquifers in hard rock environments tend to be spatially fragmented. Two wells may be situated close to each other but one might yield an ample supply of groundwater, whereas the other could be dry or offer only a minimal amount of water. The geological structure beneath these aquifers comprises of dense, impermeable rock with interspersed fractures and zones of permeable material, which act as reservoirs for groundwater. Therefore, these aquifers possess a low storage capacity, especially when compared to the alluvial aquifers found in Northern India. Their vulnerability arises from the fact that the permeable zones and fracture networks within hard rock aquifers may rapidly exhaust if groundwater withdrawal rates surpass the natural recharge capabilities of the aquifer (Blakeslee, Fishman, and

Srinivasan, 2020; Fishman et al., 2011). Thus, assessing the effects of an unrestricted power supply on groundwater resources in these terrains is crucial, and our research enhances understanding in this area.

Our contribution to the literature is substantive, with a minor methodological component. First, previous studies have examined economic drivers of groundwater depletion such as the delayed transplantation of paddy policy (Sekhri, 2012-13), procurement incentives (Chatterjee, Lamba, and Zaveri, 2024), and agricultural electricity tariffs and subsidies (Gupta, 2023; Badiani and Jessoe, 2018). Ryan and Sudarshan (2022), using primary data from Rajasthan, suggest that rationing is approximately efficient on average, though only when the depletion externality is not taken into account. Our substantive contribution examines the effect of removing electricity rationing on key outcomes of economic interest— power consumption and groundwater. We show that removal of rationing results in a large increase in agricultural power consumption that must be inefficient. We expect an effect on groundwater depletion but are unable to find one. By eliminating alternative explanations for this counterintuitive result, we conclude that the absence of observed depletion is not due to the absence of an effect, but rather due to limitations in the monitoring practice. Specifically, placing monitoring wells away from farmer wells may be adequate for alluvial aquifers but is inappropriate for hard rock aquifers when it comes to detecting depletion in economically important farmer wells. This has important implications for both energy and water policy, and is a major and novel contribution of our paper. Second, we also make a methodological contribution by incorporating a matching method in our estimation. We implement a difference-in-differences design that incorporates the idea of a geographic regression discontinuity with segment fixed effects, which allows us to overcome a problem of comparability in two dimensions—the fact that wells may be close in terms of one-dimensional distance from a state boundary, yet still be far apart spatially, and therefore not good controls for each other. This methodological refinement enhances the robustness of our estimates and offers a replicable strategy for future studies dealing with spatial discontinuities in environmental and policy research.

The key assumption needed for identification is that the only change over time in the

differences across the boundary is the removal of rationing of electricity in Telangana. We are not able to fully identify this effect, however, because Telangana was also increasing the infrastructure for state procurement of rice during these years, possibly increasing water demand through channels such as a crop switch to rice and new tubewell connections, in addition to the power supply channel. Accordingly, we identify the combined effect of the change in power policy and the increase in rice procurement, with the power policy being the primary driver of this effect. We are able to control for other significant state-specific changes, particularly in irrigation infrastructure.

We assembled a district-level monthly panel on agricultural power consumption for Telangana and neighboring districts in boundary states. Using this panel data and a difference-in-differences approach, we find that agricultural power consumption in Telangana increased by approximately 53 percent in the months following the removal of rationing. However, using the geographical difference-in-differences, we do not find an increase in groundwater depth in government monitoring wells in Telangana compared to neighboring states in the two years following the policy change. Nor do we see an increase in missing data that might arise from an increase in the number of wells going dry. However, state-level data show an increase in kharif (monsoon) and rabi (winter) rice cultivation, a major and water-intensive crop in Telangana, post-policy, indicating a rise in groundwater extraction for irrigation. Finally, we explain that the combined prevalence of these observed outcomes—particularly absence of an effect on groundwater depth and missing wells that may have gone dry—can best be explained by the disconnect between monitoring wells and farmer wells.

The structure of the paper is as follows: Section 2 describes the data sources and descriptive statistics. Section 3 outlines the identification and estimation process, providing detailed results on agricultural power consumption, groundwater depth, and dry wells. It also explores heterogeneity and performs robustness checks on groundwater outcome. Section 4 explores the underlying mechanisms behind the observed effects. We summarise our findings and their implications in Section 5.

2.2 Data

This study uses monthly spatial point data on groundwater depth from the India Water Resource Information System (INDIAWRIS),[3] for Telangana and its boundary states—Andhra Pradesh, Karnataka, and Maharashtra. The Central Ground Water Board (CGWB) and State Groundwater Departments (SGWD) collect this data using a large set of wells used exclusively for monitoring. The data includes measurements of groundwater depth in meters below ground level (mbgl), along with geographical coordinates of the monitoring wells. SGWD data is collected monthly, while CGWB data is collected quarterly (generally in May, August, November and January). Monitoring is non-uniform both spatially and temporally, with irregularly spaced wells that change in quantity across locations and over time (Ali and Arora, 2021). We exclude monitoring wells within 5 km on each side of the boundary to account for potential aquifer connectedness at the state boundary. We include only monitoring wells within 32.18 km, as these wells share similar associated characteristics, and this cutoff is based on the optimal bandwidths derived from the regression discontinuity method in Appendix Model 2.3. The boundary dataset, spanning 5 to 32.18 km on both sides of the state boundary, includes records from 1658 monitoring wells collected between January 2014 and December 2019.

Precipitation and temperature data for this study are taken from the European Centre for Medium-Range Weather Forecasts, featuring a 0.1 by 0.1-degree (approximately 11 x 11 km) spatial resolution. This climatic data is matched with monthly groundwater depth data using point-level geographical coordinates, resulting in a panel dataset of 1658 monitoring wells spanning January 2014 to December 2019. The dataset is unbalanced due to missing groundwater depth observations for some periods. We assume these missing values as indicators of dry wells to assess whether the fraction of dry wells increases following the policy implementation.

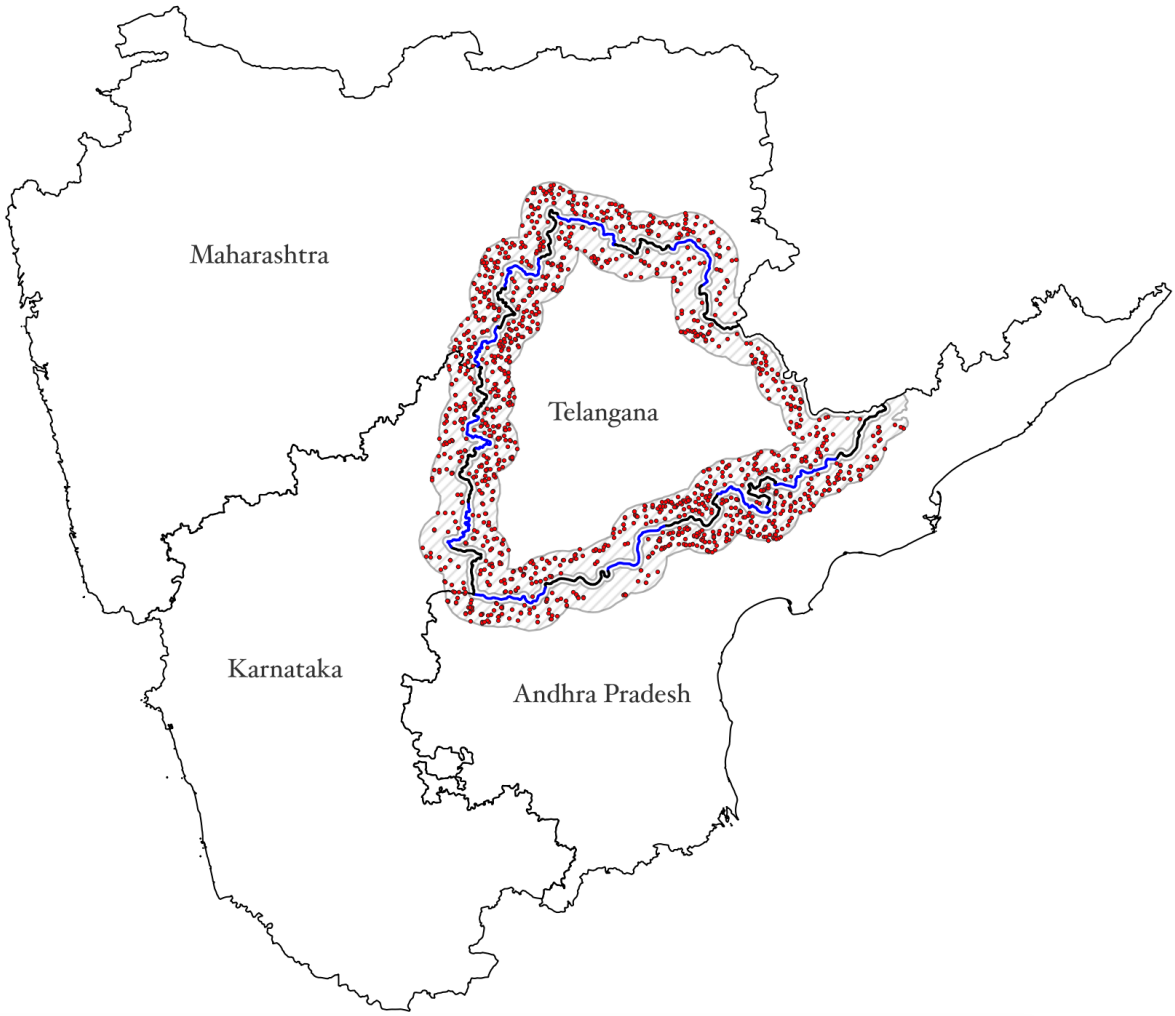
We divide the Telangana boundary into 21 segments, each approximately 100 kilometers in length (ranging from 97 km to 105 km), and refer to them as 'boundary segments'.

[3] https://indiawris.gov.in

This enables us to compare monitoring wells within a segment area and thereby close and similar in all characteristics like aquifer type, access to road and market, altitude, land type, proximity to surface water bodies, and so on. The variation in the length of the segments arises because each boundary segment is derived from only one of the neighboring states. For example, the Telangana-Maharashtra boundary spans 778 km, so we split it into segments of approximately 98 km each. Next, we calculate the 'distance' variable as the shortest distance from each well to the nearest boundary segment, which is used to select the boundary data.[4] Figure 2.3 shows boundary wells spanning 5 to 32.18 km on both sides of the boundary segments. Monitoring wells are distributed fairly evenly, except in certain areas of Andhra Pradesh. The boundary segments are represented by blue and black colors.

[4]Division of Telangana boundary into segments and calculation of the distance variable was done using QGIS software.

Figure 2.3. Monitoring wells spanning 5 to 32.18 km on both sides of the boundary segments



Notes: There are 1,658 monitoring wells located within 5 to 32.18 km on both sides of the boundary segments, as indicated by red dots within the hatched lines. There are 21 Telangana boundary segments, indicated by blue and black colors. The lengths of the segment curves range from 97 km to 105 km. We exclude the state of Chhattisgarh, located to the northeast of Telangana, because of insufficient data.

Source: State shapefile is downloaded from gadm.org. Monitoring well data is downloaded from INDIAWRIS.

In addition, we utilise monthly boundary district data on agricultural power consumption from Telangana and its neighboring states (Andhra Pradesh, Karnataka, and Maharashtra) to examine the impact on agricultural power consumption.[5] Agricultural power consumption data for nine boundary districts of Telangana and fourteen boundary districts from neighboring states are obtained from the respective state power distribution

[5]Agricultural power is mainly used for groundwater irrigation, with 1,550,929 groundwater schemes (wells) versus 36,282 surface water schemes, as reported by the Sixth Minor Irrigation Census (2017-2019). Numerous studies indicate that nearly all electricity classified as 'agricultural' by the Ministry of Power or the Ministry of Agriculture and Farmers' Welfare is used for groundwater irrigation (Barik et al., 2017; Birner, Gupta, and Sharma, 2011).

companies.[6] The gridded precipitation and temperature data are spatially averaged at district level to match with the district-wise agricultural power consumption data for quantitative analysis.

We also use data on the area under water intensive rice cultivation from the Directorate of Economics and Statistics, Ministry of Agriculture, for Telangana and its neighboring states. This data helps to show an increase in groundwater usage for irrigation in Telangana.

To complement our analysis of secondary data, the first author conducted field visits to eight villages and various departmental offices across numerous districts in both northern and southern Telangana in December 2022. Through these visits, it was possible to directly interact with local farmers, departmental officials, and local researchers. This visit is instrumental in explaining our secondary data insights, offering a holistic view of the topic.

Table 2.1 presents the descriptive statistics for the outcome and control variables in both treatment and control states during the pre and post-policy periods. Although there were no significant changes in groundwater depth in Telangana before and after the policy, there was a noticeable increase in agricultural power consumption. In contrast, the groundwater depth in neighboring states increased after the policy by more than a meter, mainly driven by Andhra Pradesh probably because of precipitation, while agricultural power consumption in Andhra Pradesh remained relatively stable.

[6]Map for boundary states and districts, including the pilot policy districts, are shown in Appendix Figure 2.11.

Table 2.1. Descriptive statistics

	Groundwater depth (mbgl)		Power consumption (MWh)		Precipitation (mm)		Temperature (°C)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Telangana	9.25	9.65	114.3	183.64	81.63	92.06	27.38	27.3
Non Telangana	10.23	11.46	51.64	52.82	83.67	88.37	27.53	27.65
Andhra Pradesh	11.33	12.73	69.23	69.23	81.98	83.03	27.82	27.91
Karnataka	6.76	7.04	38.98	39.66	71.98	71.87	26.67	26.59
Maharashtra	6.21	5.99	38.47	44.71	90.06	101.36	27.45	27.66

Notes: These values are monthly averages for Telangana and neighboring states. Groundwater depth, precipitation and temperature correspond to areas within 5 to 32.18 km on both sides of the boundary and agricultural power consumption figures are for boundary districts. The post period for Telangana starts in July 2017 for pilot districts and January 2018 for the remaining districts, whereas the post period for non-Telangana regions begins in January 2018. Number of observations for our outcome variables are given below:
Groundwater depth: Telangana - Pre 11043 Post 7709; Non Telangana - Pre 9701 Post 5153
Power consumption: Telangana - Pre 369 Post 216; Non Telangana - Pre 410 Post 186

Table 2.2 presents the descriptive statistics for our secondary variables: the dummy for missing observations in CGWB and SGWD data (analysed separately) and the kharif and rabi rice areas. The dummy for missing observations in CGWB and SGWD data is conditional on all non-missing observations for the November 2016 quarter and month, respectively. We strategically selected November 2016 as it is a post-monsoon month when most of the monitoring wells are expected to be active. The results show no significant change in the percentage of missing observations in CGWB and SGWD data in Telangana, indicating no notable shift in the prevalence of dry wells. However, there is a substantial increase in both kharif and rabi rice areas in Telangana. Given that rice is a water-intensive crop and a major component of agriculture in Telangana, combined with the significant reliance on groundwater for irrigation in Telangana, it suggests a high level of groundwater extraction for irrigation purposes. We explore and discuss these phenomena in detail in the following sections: Estimation and Results, and Mechanism.

Table 2.2. Secondary variables

	CGWB missing (Yes = 1)		SGWD missing (Yes = 1)		Kharif rice area (Mha)		Rabi rice area (Mha)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Telangana	0.05	0.13	0.01	0.01	0.9	1.41	0.58	0.83
Non Telangana	0.08	0.11	0.02	0.02	1.3	1.33	0.24	0.24
Andhra Pradesh	0.05	0.07	0.02	0.02	1.51	1.55	0.7	0.69
Karnataka	0.12	0.18	-	-	0.91	1	0.03	0.02
Maharashtra	0.07	0.07	-	-	1.47	1.45	-	-

Notes: The dummy for missing observations in CGWB and SGWD data is based on all non-missing observations for the November 2016 quarter and month. Rice area figures are annual averages. The post period for Telangana begins in July 2017 for pilot districts and in January 2018 for the rest of Telangana, while the post period for non-Telangana regions starts in January 2018.

2.3 Estimation and Results

One effect of the policy change is expected to be an increase in pumping hours per day. This is likely to result in higher agricultural power consumption in Telangana compared to neighboring states after the policy. This effect is expected to be immediate as it primarily involves existing pump connections. Another effect of the policy change is likely to be an increase in new electric pump connections that may take longer to materialise but would result in a further increase in agricultural power consumption. The increase in power consumption is likely to increase the groundwater depth and increase in the probability of well failures, particularly in hard rock aquifers of Telangana that have limited storage, which is a cause for concern.

2.3.1 Impact on agricultural power consumption

We utilize district-level monthly agricultural power consumption data that we assembled from various state-owned distribution companies to investigate the effect of the policy change on agricultural power consumption. We estimate a model using data from the nine (out of ten) boundary districts of Telangana and the boundary districts from its neighboring states. We limit our analysis to these boundary districts since they are better controls. The identifying assumption is that, controlling for precipitation and temperature, changes over time in variables other than the power policy are identical for these boundary

districts. In fact, Telangana improved rice procurement infrastructure, with procurement increasing to an unprecedented level in 2019, 1.5-2 years after the power policy change. We thus estimate a combined effect of the two changes, with the power policy being the primary driver of this effect. This is discussed further below. We use the following event-study-type regression specification:

$$Y_{dt} = \mu_d + \eta_t + \sum_{k \neq -1} \tau^k D_{dt}^k + X_{dt} + \epsilon_{dt} \tag{2.1}$$

where Y_{dt} denotes the agricultural power consumption in district d in month-year/time t. t ranges from January 2014 to December 2019. D_{dt}^k is an event-month indicator variable that equals 1, if treated district d at time t is k months away from the treatment month-year (July 2017/January 2018), and 0 otherwise. τ^k are our coefficients of interest that capture the residual difference in outcomes relative to the month before the treatment. District fixed effects μ_d, and time fixed effects, η_t, account for unobserved heterogeneity across districts and time respectively. We include precipitation, temperature, and their six lags as control variables, denoted as X_{dt}. Standard errors are clustered at the district level to account for serial correlation.

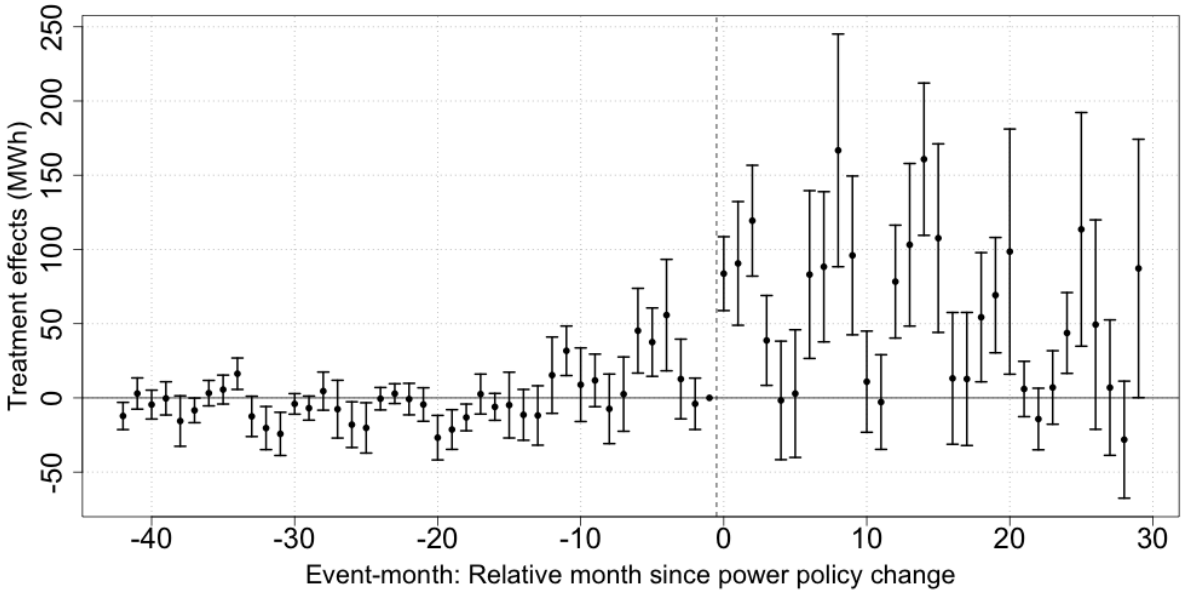
We have staggered treatment, with the pilot starting in July 2017 and the full rollout in Telangana in January 2018. Conventional difference-in-differences estimates are prone to bias in settings with staggered treatment rollouts and heterogeneous treatment effects. In the presence of such heterogeneity, OLS models may yield biased results and lead to incorrect conclusions due to negative weights being assigned to some individual treatment effects. Recent advances in econometric literature have highlighted these concerns (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Borusyak, Jaravel, and Spiess, 2024; Sun and Abraham, 2021; Wooldridge, 2021; Gardner, 2022). We follow (Gardner, 2022) and use the associated R package developed by Butts and Gardner (2021).[7] Using this method, outcomes

[7]Based on the comparative table in (Wing et al., 2024), which reviews multiple approaches and software for robust estimation under staggered adoption, we selected (Gardner, 2022) as our preferred approach. It accommodates time-varying covariates, such as precipitation and temperature, which are crucial in our context.

are regressed on district and month-year fixed effects, and control variables, using the subsample of untreated/not-yet-treated observations in the first stage. In the second stage, the resulting residualised outcomes are regressed on treatment status in the full sample to get Average Treatment Effects on the Treated (ATTs) for each k.

Point estimates for the event-month indicator variable from (Equation 2.1) are shown in Figure 2.4. All coefficients are shown relative to the event-month -1, the month just before the treatment. Treatment effects remain roughly constant prior to event-month 0, with a few exceptions, thereby supporting the parallel trends assumption. There is an overall increase in the treatment effects post-policy indicating that the removal of rationing from 9 hours of daily power supply to 24 hours per day resulted in a significant increase in agricultural power consumption. We observe fluctuations in the coefficients due to seasonality in crop growing seasons. For instance, peak agricultural power consumption mostly coincides with March, which corresponds to the panicle formation stage of rabi (winter) rice that requires the highest amount of irrigation. The average treatment effect of the policy is calculated using Equation 2.1, where the indicator variable now equals 1 if district d at month-year t has received the treatment, and 0 otherwise. The coefficient τ is now 60.12 (SE 15.34) in Table 2.3, a statistically significant and roughly 53-percent increase in agricultural power consumption compared to the baseline agricultural power consumption of Telangana. Additionally, OLS estimates of equation 2.1 show a similar pattern (Appendix Figure 2.19), with an average treatment effect of 59.49 (SE 15.39). Our results remain robust when using each neighboring state separately as a control group (Appendix Figures 2.14, 2.16 and 2.15). This indicates that the observed increase in agricultural power consumption post-policy is driven solely by Telangana's power policy and not by changes in other states. Two separate event studies, one comparing the pilot districts in Telangana to the untreated districts in non-Telangana states, and another comparing the remaining districts in Telangana to the untreated districts in non-Telangana states, show a similar pattern (Appendix Figures 2.17 and 2.18).

Figure 2.4. Impact on agricultural power consumption



Notes: Agricultural power consumption in Telangana boundary districts is compared with that in non-Telangana boundary districts to evaluate the impact of the power policy. We estimate the coefficients specified in equation 2.1 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include district and time fixed effects. We cluster at the district level. The baseline mean agricultural power consumption in Telangana is 114.3 MWh. The dataset comprises 23 districts and 1,518 observations.

The expansion of surface water lift irrigation (the Kaleshwaram project launched in 2018) could also contribute to the overall increase in agricultural power consumption. But the share of surface water schemes powered by electricity compared to groundwater schemes (wells) powered by electricity is only 2.3%, so this can explain only a very small proportion of the effect.[8] As further evidence, there appears to be no differential increase in agricultural power consumption in Medak (a district that is wholly covered by the Kaleshwaram lift-irrigation project) post-policy compared to other districts in Telangana (Appendix Figures 2.12 and 2.13).

As pointed out in the introduction, Telangana has increased its rice procurement infrastructure, leading to more rice being procured in some years during our study period (Appendix Figure 2.24). However, increased procurement to support higher production occurred for the first time only in the agricultural year 2018-19 (July 2018 to June 2019),

[8]The medium and deep tubewells that account for 62% of all schemes (Appendix Figure 2.23), have command areas comparable to those of surface lift schemes powered by electricity (*Sixth Census of Minor Irrigation Schemes* 2017-19, p. 499-501).

see Appendix Figure 2.24. This could not have had an effect on power demand before the second half of 2018 when *kharif* rice was planted. But we do see increased agricultural power consumption in the first four months after the introduction of the policy—July 2017 in three districts and January 2018 in the remaining seven districts—in Figure 2.4. It is also worth noting that while improved procurement may have contributed to the increase in power consumption in later months, it could not have done so without a relaxation of rationing. The only other way the extra water to grow the additional rice could have been obtained is via a large increase in the number of tubewells. But the number of new wells increased by only about 100,000 per year from 2015 to 2019 (less than 5% per year) with no jump in the trend (Sreekumar, 2020). This is far too small to account for the 50% increase in power consumption.

2.3.2 Impact on groundwater depth

We utilise geographic information from monitoring wells to estimate a difference-in-differences model. The threshold we use takes the form of a two-dimensional curve rather than a single point as in standard regression discontinuity designs. This presents a challenge, as two wells situated close to the Telangana boundary may be far apart from each other spatially and therefore exhibit significant variation in unobserved trends. This can introduce bias if wells are not evenly distributed along the boundary. To address this issue, we leverage the spatial nature of our data and partition the long Telangana boundary into segments. By utilising segment fixed effects, we can exploit the variation in wells within each segment and compare wells in close proximity that share similar characteristics, such as aquifer type, access to road and market, altitude, land type, proximity to surface water bodies, thus minimizing the likelihood that differential trends related to these characteristics could bias our results. We use wells within 5 to 32.18 km of the state boundary on both sides of the boundary. We exclude wells within 5 km on each side of the boundary to account for potential aquifer connectedness close to the state boundary. We include only wells within 32.18 km,[9] since wells near each other are

[9]We average the bandwidth from each month from repeated geographic regression discontinuity models (Appendix equation 2.3). This average bandwidth, determined to be 32.18 km, is then employed

more likely to have similar characteristics and trends. The identifying assumption is that, controlling for precipitation and temperature, changes over time in variables other than power policy near the boundary are identical on both sides of the boundary. We use an event-study specification similar to that used for the impact on power consumption.

$$Y_{ist} = \mu_s + \eta_t + \sum_{k \neq -1} \tau^k D^k_{ist} + X_{ist} + \epsilon_{ist} \tag{2.2}$$

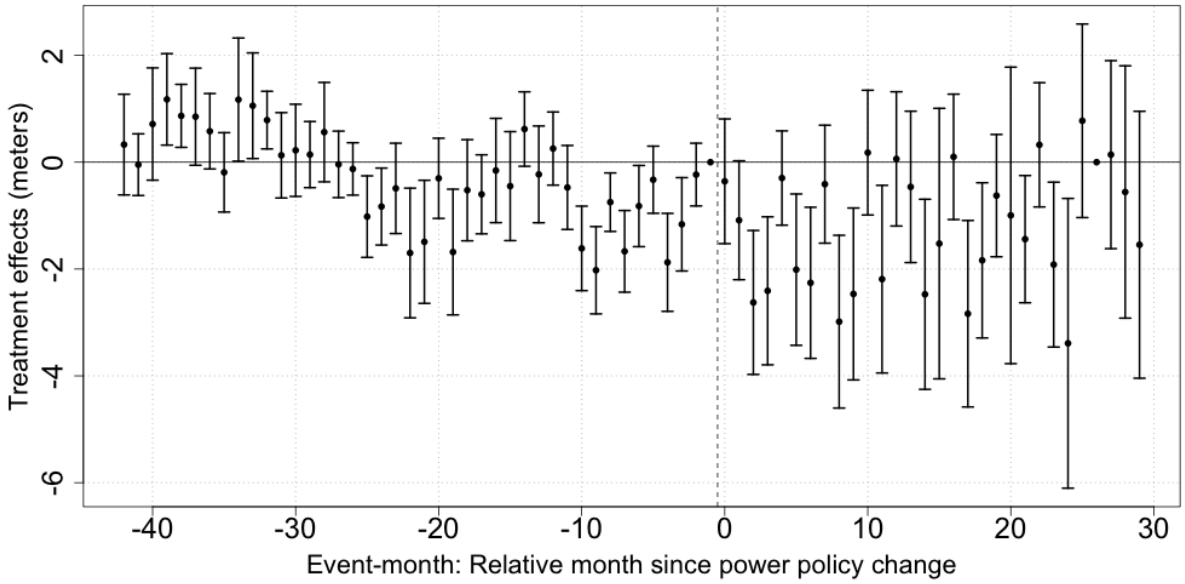
where Y_{ist} denotes the groundwater depth at well i, which is closest to boundary segment s, in month-year t. t ranges from January 2014 to December 2019. D^k_{ist} is an event-month indicator variable that equals 1, if well i in treated districts at time t is k months after from the treatment month-year (July 2017/January 2018), and 0 otherwise. τ^k are our coefficients of interest that capture the residual difference in outcomes relative to the month before the treatment. As explained in the previous section (Section 2.3.1), we follow Gardner (2022) to account for dynamic treatment effects. Segment fixed effects μ_s, and time fixed effects, η_t, account for unobserved heterogeneity across segments and time respectively. X_{ist} denotes our control variables - precipitation, temperature, and their six lags. Standard errors are clustered at the well level to account for the correlation of errors across different time periods.

Point estimates for the event-month indicator variable from Equation 2.2 are shown in Figure 2.5. All coefficients are shown relative to the event-month -1, the month just before the treatment. Groundwater depth decreased during the pre-treatment period. However, periods from event-month -24 to -2, which are closer to the treatment month and crucial for supporting the parallel trends assumption, exhibit a relatively stable trend. Comparing these pre-policy event-months with post-policy periods, we observe no clear or differential trend in treatment effects, suggesting that groundwater depth did not undergo significant changes post-policy. OLS estimates of equation 2.2 show a similar pattern (Appendix Figure 2.20). The average treatment effect of the policy τ is calculated by replacing the term $\sum_{k \neq -1} \tau^k D^k_{ist}$ in Equation 2.2 with τD_{ist} where the indicator variable

to estimate the geographical difference-in-differences model, equation 2.2. Additionally, for sensitivity tests, we select alternative bandwidths to examine the robustness of our results.

now equals 1 if well i at month-year t has received the treatment, and 0 otherwise. We show the average effect of the power policy on groundwater depth along with agricultural power consumption in Table 2.3.

Figure 2.5. Impact on groundwater depth



Notes: Groundwater depth within 5 to 32.18 km of the boundary in Telangana is compared with that in non-Telangana states to assess the impact of the power policy. We estimate the coefficients specified in equation 2.2 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include segment and time fixed effects. We cluster at the well level. The baseline mean groundwater depth in Telangana is 9.25 meters below ground level. The dataset comprises 1585 wells and 30211 observations.

Column 1 shows the significant increase in agricultural power consumption in Telangana following the power policy, roughly a 53-percent increase compared to the baseline agricultural power consumption of Telangana. However, contrary to our hypothesis, Columns 2-5 don't show a significant increase in groundwater depth in Telangana after the policy. Columns 4 and 5 replace segment fixed effects with well fixed effects. All estimates, except for Columns 3 and 5, are based on all pre-policy event-months depicted in Figure 2.5. In Columns 3 and 5, we restrict our sample to observations from January 2016 onwards, closer to the treatment month, where the pre-trend is stable, and find that the impact of the policy on groundwater depth is statistically insignificant.

Table 2.3. Impact on agricultural power consumption and groundwater depth

	(1) Power consumption (MWh)	(2) Groundwater (meters)	(3) Groundwater (meters) (Jan 16 onwards)	(4) Groundwater (meters)	(5) Groundwater (meters) (Jan 16 onwards)
Treatment = 1	60.12***	-1.12*	-0.71	-0.43**	0.16
SE	(15.34)	(0.57)	(0.58)	(0.14)	(0.11)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	District	Segment	Segment	Well	Well
Cluster	District	Well	Well	Well	Well
Bandwidth	Boundary districts	5-32.18 km	5-32.18 km	Boundary districts	Boundary districts
Districts/Wells	23	1,585	1,585	5,802	5,802
Observations	1,518	30,211	22,911	117,180	88947
Adjusted R^2	0.21765	0.003	0.001	0.002	0.0002

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: We estimate the average treatment effect of the power policy using a staggered DiD approach, following Gardner (2022). We control for precipitation, temperature, and their six lags. We include time fixed effects. In columns 3 and 5, we restrict our sample to observations from January 2016 onwards, closer to the treatment month, where the pre-trend is stable.

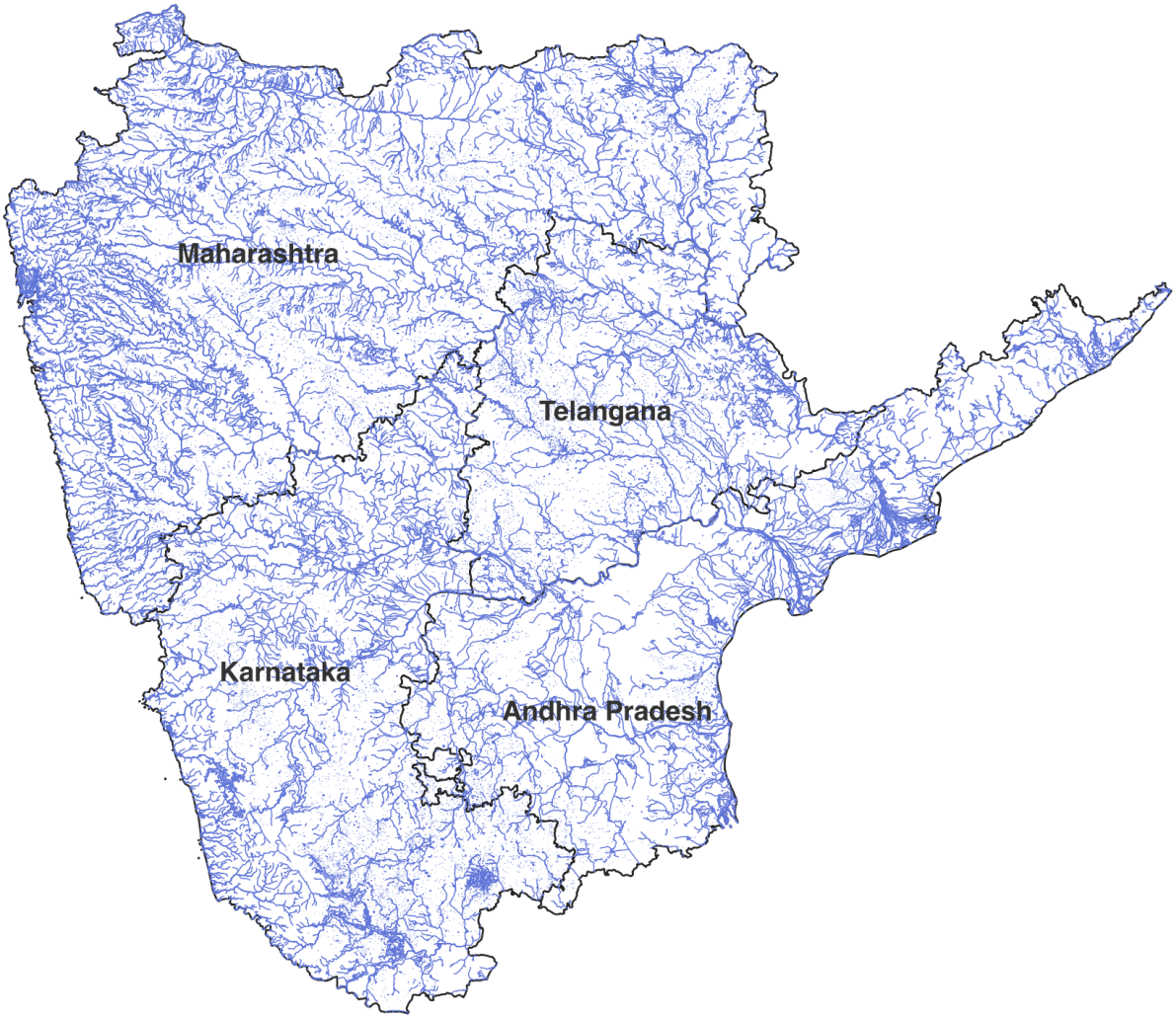
Groundwater flows laterally in response to pressure changes. If it crosses the state boundary then the policy in Telangana could also result in depletion across the state boundary and bias our result towards zero. However, in Telangana and southern India more generally, the fragmented nature of hard rock aquifers makes this highly unlikely as can be seen from the following two examples. First, panel B in Appendix Figure 2.27 (adapted from Blakeslee, Fishman, and Srinivasan (2020)) shows 450 borewells within a 5 km horizontal scale, covering an area of approximately 20 km^2. Given that these borewells include a mix of active and dry wells with some right next to each other, we infer that the hard rock aquifer even in this small region is not well-connected. Second, a figure from hydrogeology studies by Guihéneuf et al. (2014) and Maréchal et al. (2018) that focus on the Experimental Hydrogeological Park (EHP) near Choutuppal village in the Nalgonda district of Telangana and the Maheshwaram watershed (53 km^2) near Hyderabad in Telangana, respectively, clearly illustrates the discontinuous nature of the aquifer during the pre-monsoon season on a horizontal scale of 200 meters (Appendix Figure 2.25).

2.3.3 Heterogeneity and robustness checks

2.3.3.1 Closeness to surface water bodies

Surface water networks and groundwater networks are generally interconnected both within and beyond state boundaries. Over time, the network of surface water in Telangana has grown, enhancing the recharge of groundwater in nearby regions. As explained in Section 2.3.2 above, hard rock aquifers in Telangana are localised and fragmented. So, recharge through these water bodies are local and confined to nearby aquifers. Figure 2.6 depicts the widespread distribution of the surface water network, including rivers, canals, reservoirs, streams, tanks, and drains, across five states.

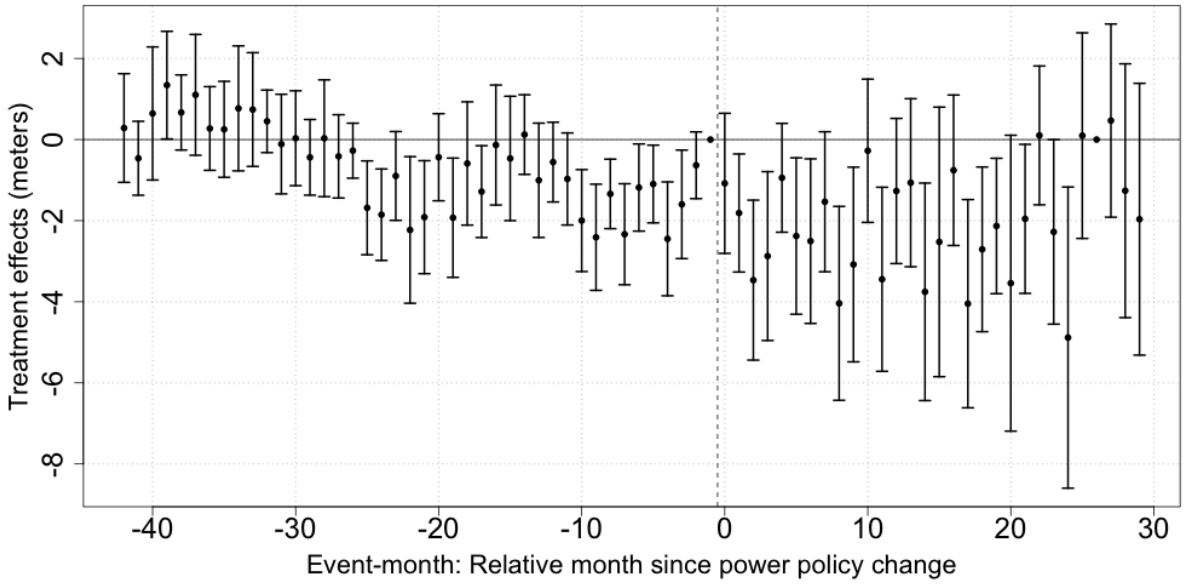
Figure 2.6. Surface water network in Telangana and neighboring states



Notes: We have obtained the surface water network files from OpenStreetMap as on May 19, 2022, which include data on rivers, canals, reservoirs, streams, and drains.

To exclude extensions of the surface water network that could reduce groundwater depth and so bias our results, we exclude wells within 1 km of surface water and re-estimate Equation 2.2 on groundwater. We obtained geocoded data on the surface water network as of May 19, 2022, that includes all water bodies from OpenStreetMap. Therefore, this exercise accounts for groundwater recharge due to the matured stage of the Kaleshwaram lift irrigation (a surface water network expansion program launched in 2018) and Mission Kakatiya (a phased tank revival scheme launched in 2014). After excluding wells within 1 km of the surface water network, we see a pattern of treatment effects on groundwater depth in Figure 2.7 that is similar to that seen in the whole sample in Figure 2.5, without a differential increase in groundwater depth after the policy. Additionally, we check the sensitivity of our results for multiple cut-off distances from the surface water network and show that the average treatment effect on groundwater depth remains insignificant (Appendix Figure 2.26).

Figure 2.7. Impact on groundwater depth for monitoring wells located at least 1 km away from surface water bodies (rivers, lakes, reservoirs, tanks, canals, etc.)



Notes: Groundwater depth in monitoring wells within 5 to 32.18 km of the boundary in Telangana is compared with that in non-Telangana states to assess the impact of the power policy. We estimate the coefficients specified in Equation 2.2 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include segment and time fixed effects and cluster at the well level. The baseline mean groundwater depth in Telangana is 9.25 meters below ground level. The dataset comprises 865 wells and 16,367 observations.

Table 2.4. Impact on groundwater depth by deep and shallow wells

	Groundwater depth (meters)	
	(1) Deep	(2) Shallow
Treatment = 1	-1.680	-0.4421
SE	(1.444)	(0.4324)
Bandwidth	5-32.18 km	5-32.18 km
Wells	111	444
Observations	4,835	12,706
Adjusted R^2	0.00425	0.00151

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: We estimate the average treatment effect of the power policy using a staggered DiD approach, following Gardner (2022). We control for precipitation, temperature, and their six lags. We include segment and time fixed effects. Deep wells have groundwater depth greater than 9 meters. Shallow wells have groundwater depth less than 9 meters. We use 32.18 km bandwidth around the boundary. We cluster at the well level.

2.3.3.2 Groundwater depth category

There are variations in recharge time for aquifers of different depths. Also, farmers tend to shift from centrifugal pumps to tubewells (high capacity pumps) at a well depth of around 8 to 10 meters (Boudot-Reddy and Butler, 2024). To account for this, we categorise wells into two types: shallow wells and deep wells, using a 9-meters cut-off for January 2014 observations. Shallow wells have a shorter recharge time from surface water or precipitation, while deep wells require more time to recharge. Some wells, such as fossil wells, may take years to recharge. Deep wells are at a greater risk of running dry and water extraction from these wells would be reflected in our results in the absence of temporary recharge. Our analysis using Equation 2.2 shows insignificant impact on groundwater depth for both deep and shallow wells in column 1 and column 2 of Table 2.4.

2.3.3.3 Different bandwidths

To further test our model's sensitivity to different bandwidth choices, we conduct analyses using 16 km and 64 km bandwidths. These are half and double the previously used bandwidth, respectively, as suggested by Imbens and Lemieux, 2008. The 64 km bandwidth

analysis covers almost the entire state of Telangana. We don't see a significant increase in groundwater depth post-policy across the various choices of bandwidths in Table 2.5.

Table 2.5. Impact on groundwater depth for various bandwidths

	Groundwater depth (meters)		
	(1)	(2)	(3)
Bandwidth	32.18	16	64
Treatment = 1	-0.5384	0.6087	-0.7570*
SE	(0.5183)	(0.6378)	(0.4136)
Wells	1,849	938	3,564
Observations	35,284	17,182	71,133
Adjusted R^2	0.00060	0.00118	0.00112

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: We estimate the average treatment effect of the power policy using a staggered DiD approach, following Gardner (2022). We control for precipitation, temperature, and their six lags. We include segment and time fixed effects. We cluster at the well level.

2.3.4 Dry wells as an outcome

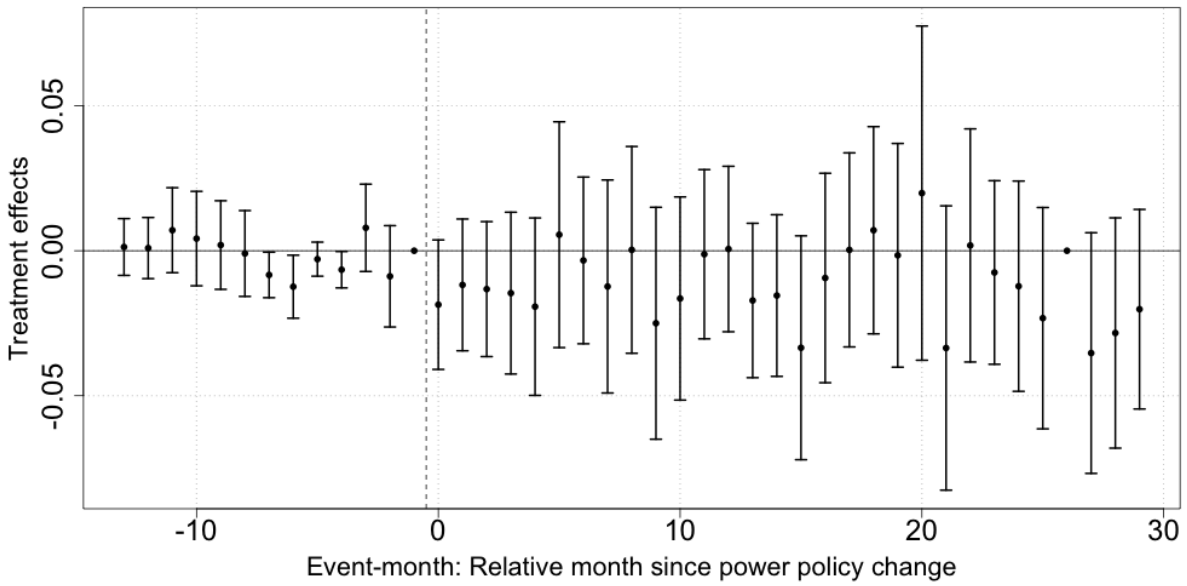
Wells could be dry or partially dry even before the policy. However, following the policy, the frequency of wells drying up may increase. While reports indicate a rise in water levels in South India in the recent decade (*Dynamic Groundwater Resources of Telangana State* 2022), there is simultaneously a growing concern among farmers regarding the occurrence of dry wells, leading to distress (Hora, Srinivasan, and Basu, 2019). It is important to note that our analysis excludes observations on dry wells by design due to missing observations, as discussed by Hora, Srinivasan, and Basu (2019) in their research paper. Missingness of groundwater observations due to dry wells or other operational reasons is not uncommon in India (Ali and Arora, 2021). However, limited studies have been conducted on dry wells due to data constraints. The findings of Hora, Srinivasan, and Basu (2019) suggest a contradiction between previous studies, which indicate an improvement in groundwater depths, and on-the-ground reports and farmer surveys, which highlight an increase in well failures. By disregarding information on dry wells, our analysis so far overlooks theoretically infinite groundwater depth, which is a significant limitation. In a study

conducted by Ali and Arora (2021) focusing on the incidence of dry wells in Uttar Pradesh, a state in North India, it is demonstrated that neglecting wells affected by dryness can lead to falsely optimistic assessments of the groundwater situation in the region. Therefore, the exclusion of dry wells in our analysis due to data limitations poses a notable drawback, as it may present an incomplete picture of the groundwater situation and hinder accurate assessments of the groundwater resource status.

In the absence of information on dry wells, if we consider missing values as indicators of dry wells, we would expect to observe an increase in the fraction of dry wells following the policy implementation. We now use a subset of groundwater monitoring wells, conditional on non-missing groundwater depth data for November 2016, using both monthly state (SGWD) and quarterly central (CGWB) data. November 2016 is strategically chosen as it is a pre-policy and post-monsoon month, ensuring that most wells are active and we retain a significant amount of data. We follow equation 2.2 on groundwater depth, where the outcome variable is now a missing dummy instead of groundwater depth. It takes the value 1, if the well observation is missing and 0 otherwise.

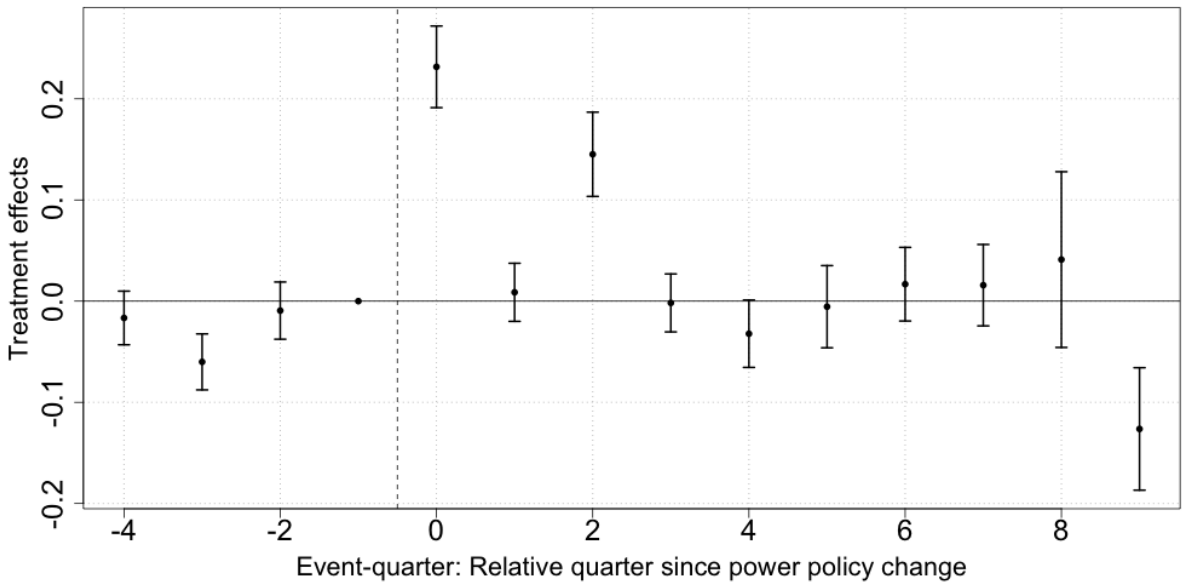
We report the point estimates for the event-month indicator variable in Equation 2.2 in Figures 2.8 and 2.9 using monthly state and quarterly central data respectively. All coefficients are shown relative to the event-month -1, the month just before the treatment. Consistent with our results on groundwater depth, almost all the treatment effect coefficients are insignificant in both the figures, indicating there is an insignificant change in the prevalence of dry wells post-policy. The point estimates for the average treatment effect of the policy are -0.010 (SE 0.014) for SGWD data and 0.018 (SE 0.026) for CGWB data, both of which are statistically insignificant.

Figure 2.8. Impact on probability of missing groundwater depth observation using SGWD monitoring wells



Notes: Missing observations (missing = 1) within 5 to 32.18 km of the boundary in Telangana is compared with that in non-Telangana state (Andhra Pradesh) to assess the impact of the power policy. The dummy for missing observations in SGWD data is based on all non-missing observations for the November 2016 month. We estimate the coefficients specified in equation 2.2 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include segment and time fixed effects. We cluster at the well level. The baseline mean of SGWD missing observations in Telangana is 0.01. The dataset comprises 338 wells and 11927 observations.

Figure 2.9. Impact on probability of missing groundwater depth observation using CGWB monitoring wells



Notes: Missing observations (missing = 1) within 5 to 32.18 km of the boundary in Telangana is compared with that in non-Telangana states to assess the impact of the power policy. The dummy for missing observations in CGWB data is based on all non-missing observations for the November 2016 quarter. We estimate the coefficients specified in equation 2.2 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include segment and time fixed effects. We cluster at the well level. The baseline mean of CGWB missing observations in Telangana is 0.05. The dataset comprises 432 wells and 5107 observations.

2.4 Mechanism

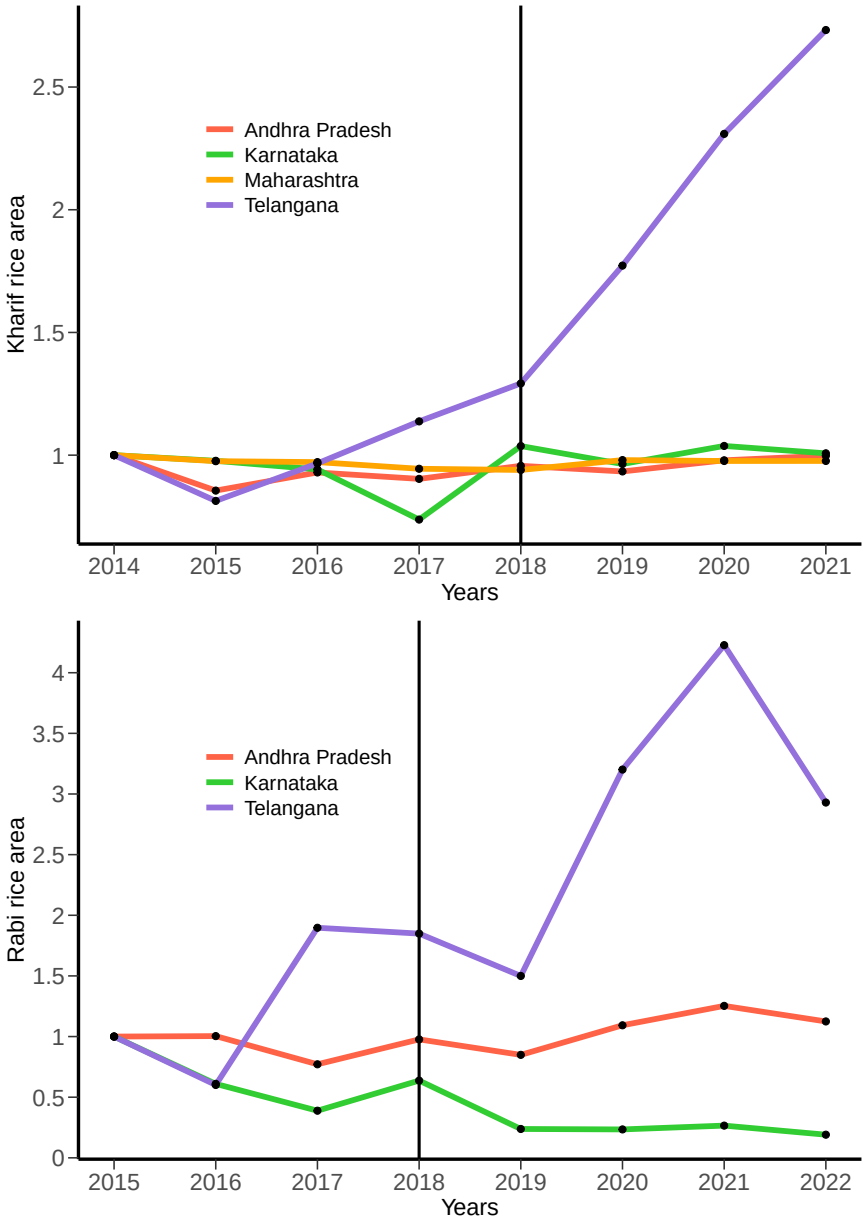
In this section, we discuss the reasons behind the groundwater depth and prevalence of missing wells remaining insignificant after the policy implementation despite the increase in agricultural power consumption.

2.4.1 Increase in groundwater extraction

Given that rationing of free power was relaxed, we would expect higher agricultural power consumption and groundwater extraction, which should lead to an increase in groundwater depth and dry wells. We do find a large increase in agricultural power consumption post-policy (Section 2.3.1) but not the expected increase in groundwater depth (Section 2.3.2). However, there is a huge increase in the area under rice, a major and highly

water-intensive crop in Telangana. The other major crop, cotton, is rain-fed (Appendix Figure 2.28). This post-policy increase in the area under rice, compared to other states (Figure 2.10), would be impossible without a large increase in groundwater use. The expansion of surface water irrigation could not account for the huge increase in rice area because the share of surface lift schemes (surface water schemes powered by electricity) is only 2.3% of the total according to the Sixth Minor Irrigation Census, conducted between 2017 and 2019 (see Appendix Table 2.23). The medium and deep tubewells that account for 62% of all schemes, have command areas comparable to those of surface lift schemes powered by electricity (*Sixth Census of Minor Irrigation Schemes* 2017-19, p. 499-501). We explain the key reason behind the insignificant change in groundwater depth in monitoring wells and dry wells in the following subsection.

Figure 2.10. Crop Area relative to the base year



Notes: Maharashtra doesn't have rabi (winter) rice cultivation. The crop calendar in India is from July to June. So 2014-15 kharif (monsoon) rice was harvested in 2014 but 2014-15 rabi rice was harvested in 2015. Years on the x-axis have been denoted according to the harvest year.

Source: Based on data from Directorate of Economics & Statistics, Ministry of Agriculture, Government of India.

2.4.2 Groundwater monitoring design

The standard practice in groundwater monitoring is to measure the 'Rest Water Level', which represents the water level once all local groundwater flows have stabilised. If there is heavy extraction, a cone of depression forms around the well, causing water from

neighboring areas to flow towards the cone. Monitoring wells are placed some distance away from farmer wells, so that the data does not reflect the depth close to farmer wells. Data from monitoring wells may indicate shallower groundwater depths compared to those reported by farmers using irrigation wells, likely influenced by local depressions near active farmer wells.

In the hard rock aquifers of southern India, aquifers are extremely localised and fragmented (explained in Section 2.3.2), and a monitoring well near a farmer well can be completely disconnected from the farmer well. Therefore, monitoring wells placed farther away are, by design, unable to capture water levels near the farmer well. Field observations by the first author support these insights, revealing significant local differences in groundwater access among farmers.

The prevailing groundwater monitoring methods, combined with the localised aquifers, fail to consistently or accurately measure groundwater depth near farmer wells. Thus, we see an insignificant impact on groundwater depth measured by monitoring wells despite the evidence discussed above in Section 2.4.1, that implies a large increase in groundwater use coincident with the policy change. Current practice for groundwater monitoring may be suitable for alluvial aquifers but it is not good enough to understand water availability for agriculture in hard rock aquifers because of the localised nature of the aquifers. Farmer wells should be systematically monitored and reported in hard rock aquifers if we are to know what is happening to agricultural water availability.

2.4.3 Misreported agricultural power consumption

Here we examine the possibility that the reported agricultural power consumption figures in Telangana could have been inflated by distribution companies after the removal of rationing.[10] Inflated agricultural power consumption could be illegally diverted to

[10]There have been instances in India where agricultural power consumption under flat tariff regimes may have been inflated by distribution companies (Sidhu, Kandlikar, and Ramankutty, 2020). Shah (2001) found that actual agricultural power use in Uttar Pradesh was 35% lower than reported. Similar overstatements were observed in Haryana, where technical and pilferage losses exceeded official figures by 10% (Shah et al., 2004). Instances of negative distribution losses have also been reported in Punjab and Maharashtra, indicating utilities claimed more power consumption by end-users than was actually distributed (Dabadge et al., 2018a).

other sectors in return for illicit payments. In this case, reported legal consumption, which is actually paid by other sectors, should have shown a corresponding decline post-policy. However, there was no corresponding decrease in industrial, commercial, or other power consumption post-policy (Appendix Figures 2.29 and 2.30). Similarly, there was no corresponding decrease in AT&C losses after the policy (Appendix Figure 2.31). Additionally, there have been negligible reports of widespread illegal diversion of agricultural power for non-agricultural use in the general media. While some instances of agricultural power theft for rice mills, poultry farms and other small-scale industrial purposes have been reported by Reddy (2019), these do not adequately explain a 53-percent increase in agricultural power consumption.

2.4.4 Underutilisation of farmer wells

Another possibility is that some of the additional power consumption was wasted in attempts to pump water from already nearly dry wells, therefore depth would not be affected.[11] However, while this may explain some of the increase in power consumption, it cannot account for the large increase in rice area, which must have increased groundwater withdrawl by a large amount.

2.5 Discussion and conclusion

By assembling a district-level panel on agricultural power consumption from state-owned distribution companies, we found that following the removal of rationing of agricultural power supply in Telangana, there was a 53% increase in agricultural power consumption.[12] This was accompanied by a large increase in the cultivation of rice, a major and water-intensive crop in Telangana, indicating a large increase in groundwater use. However,

[11] According to the 6th Minor Irrigation Census, 271,219 wells (16.77%) were underutilised in Telangana in 2017-18. Among these wells experiencing under-utilisation, inadequate water availability was the primary issue (Appendix Figure 2.32). An anecdotal report from Telangana in Appendix Figure 2.33 suggests similar underutilisation.

[12] While a minor portion of the effect can be attributed to power usage for surface water irrigation and increased rice procurement, the power policy remains the primary factor influencing agricultural power consumption.

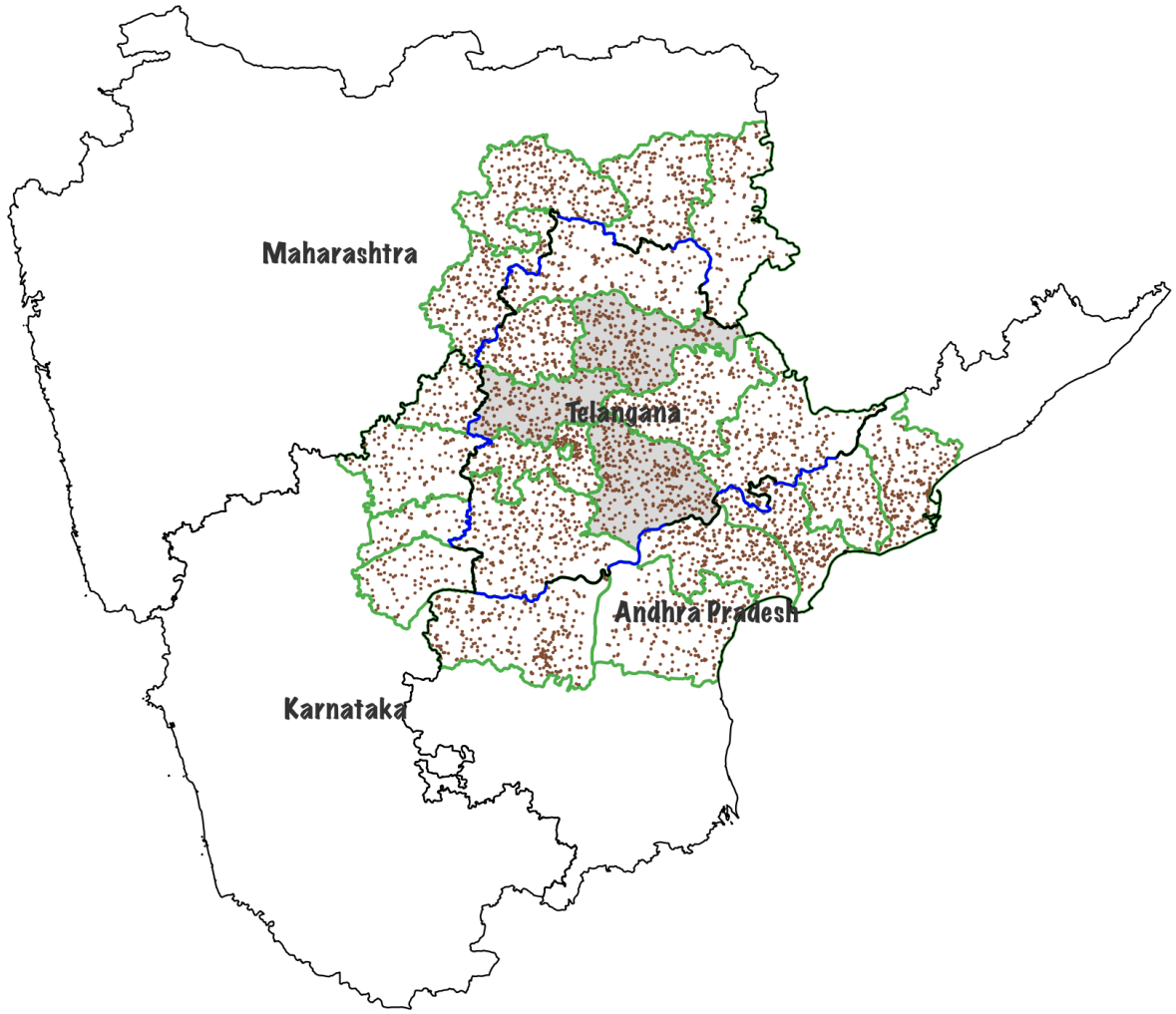
applying a geographical difference-in-differences design to panel data on government monitoring wells, we found statistically insignificant effect on groundwater depth, and nor was there an increase in the probability of missing observations in the monitoring data that might have indicated an increase in the prevalence of dry wells.

This puzzle can best be explained by the highly heterogeneous and fragmented nature of hard rock aquifers due to which monitoring wells that are deliberately placed some distance away from farmer wells can fail to pick up depletion in the localised aquifers that farmers access. This has important implications for both energy and water policy and is a major and novel contribution of our paper. The current groundwater monitoring strategy of the state and central governments should be augmented in regions with hard rock aquifers that are subject to considerable fragmentation so that groundwater—a key economic outcome—can be measured in an unbiased manner. In addition to the existing network of monitoring wells, farmer wells should be systematically monitored, both their depths, and also whether they are dry or not.

During the preparation of this work the first author used ChatGPT in order to restructure and improve sentences. After using this tool/service, the first author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

2.6 Appendix

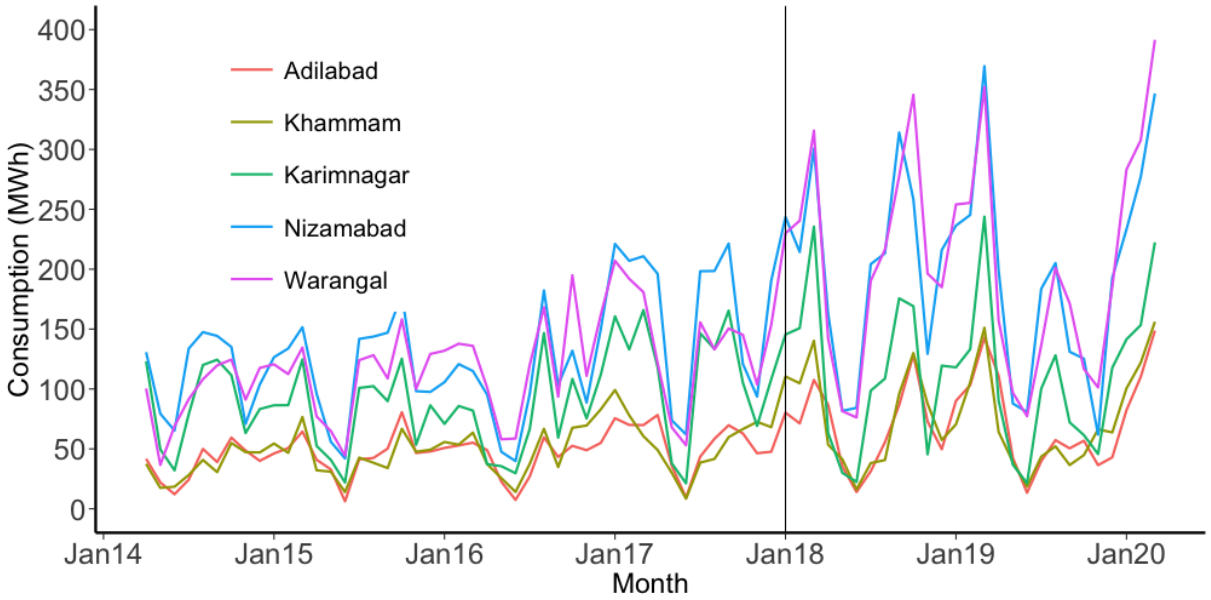
Figure 2.11. Monitoring wells located within the boundary districts



Notes: There are 5802 wells located within the boundary districts, as indicated by the red dots within the green border lines. Pilot policy districts are shaded in grey. There are 21 Telangana boundary segments, indicated by blue and black colors. The lengths of the segment curves range from 97 km to 105 km. We exclude the state of Chhattisgarh, located to the northeast of Telangana, due to insufficient data.

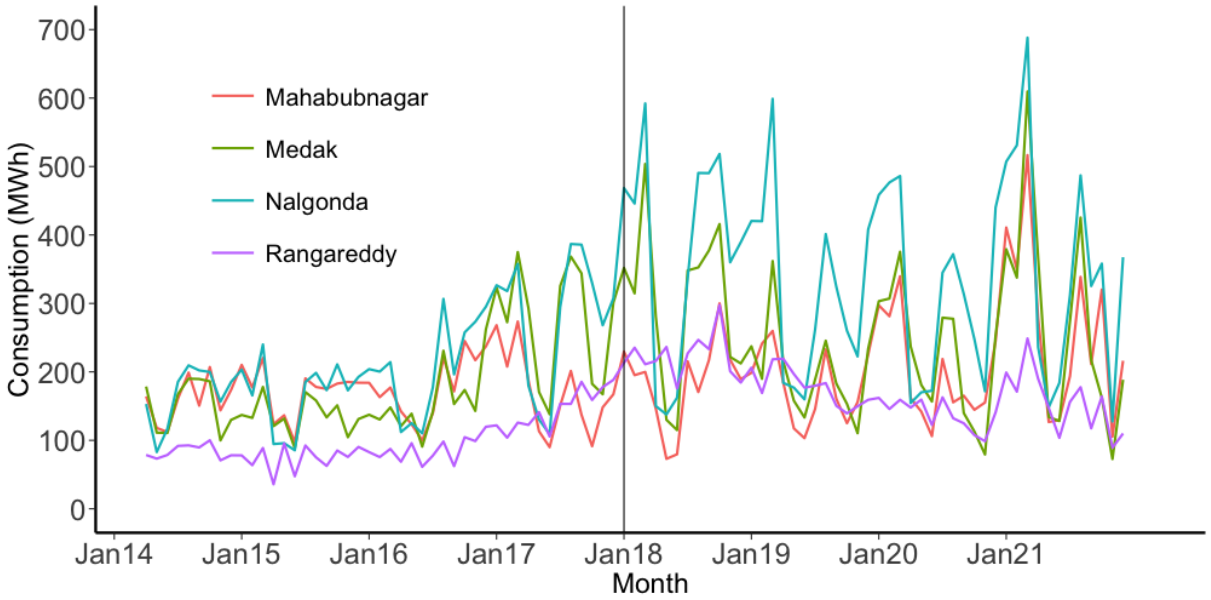
Source: State shapefile is downloaded from gadm.org. Monitoring well data is downloaded from INDIAWRIS.

Figure 2.12. North Telangana Monthly agricultural power consumption for boundary Districts



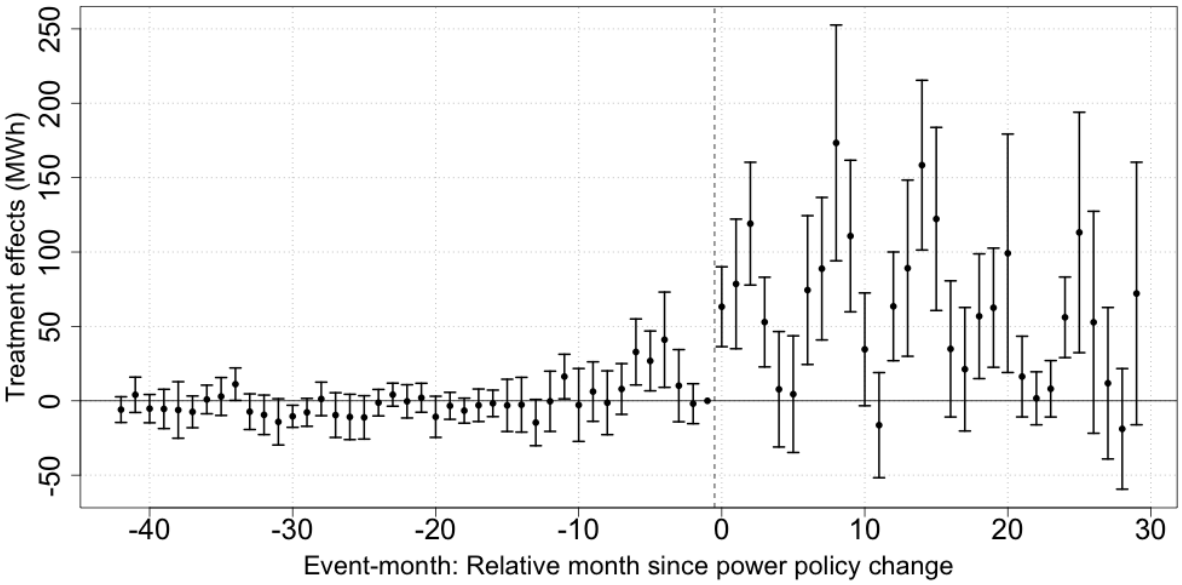
Notes: Based on data from North Telangana Power Distribution Company. Vertical line denotes the policy month. Note that the policy came six months before in Karimnagar.

Figure 2.13. South Telangana Monthly agricultural power consumption for boundary Districts



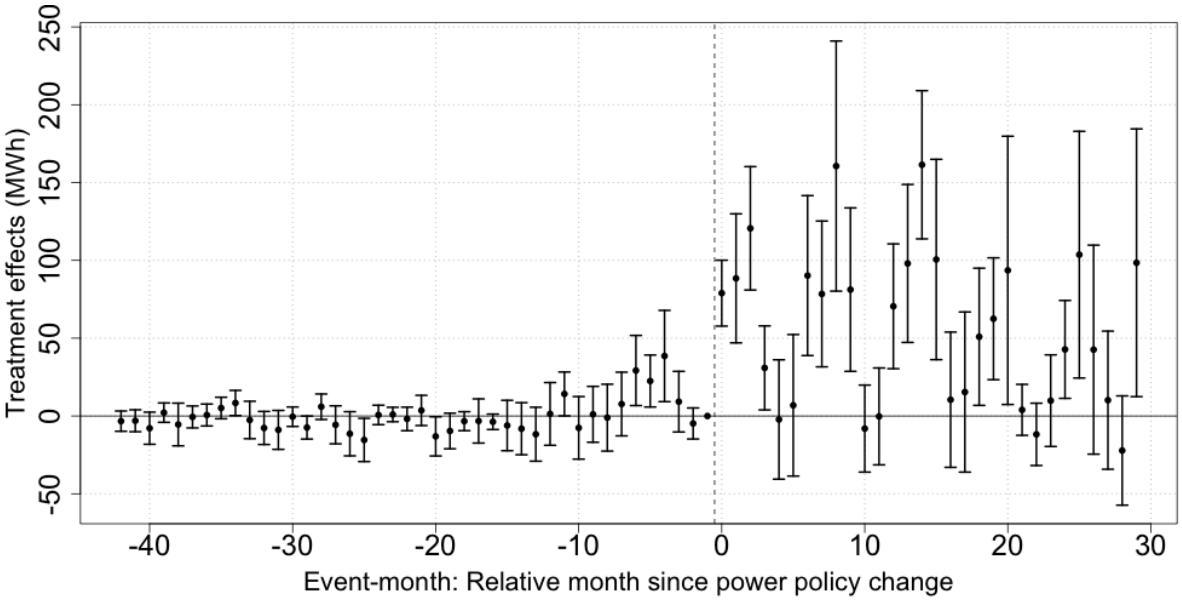
Notes: Based on data from South Telangana Power Distribution Company. Vertical line denotes the policy month. Note that the policy came six months before in Medak and Nalgonda.

Figure 2.14. Impact on agricultural power consumption (Telangana vs Andhra Pradesh)



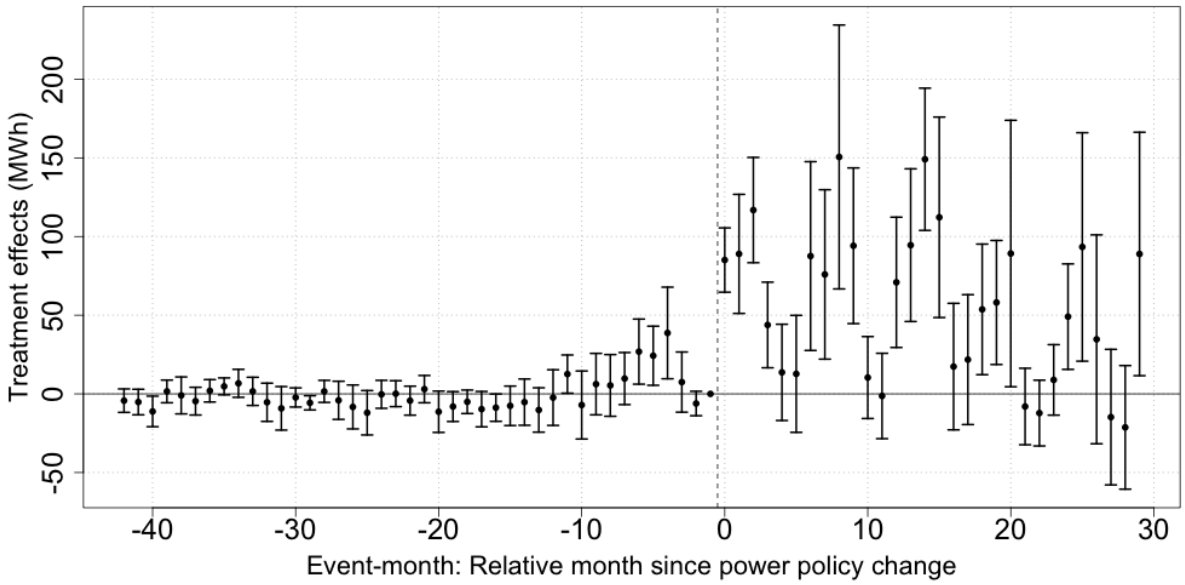
Notes: Agricultural power consumption in Telangana boundary districts is compared with that in Andhra Pradesh-Telangana boundary districts in Andhra Pradesh to evaluate the impact of the power policy. We estimate the coefficients specified in equation 2.1 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include district and time fixed effects. We cluster at the district level. The baseline mean agricultural power consumption in Telangana is 114.3 MWh. The dataset comprises 15 districts and 990 observations.

Figure 2.15. Impact on agricultural power consumption (Telangana vs Karnataka)



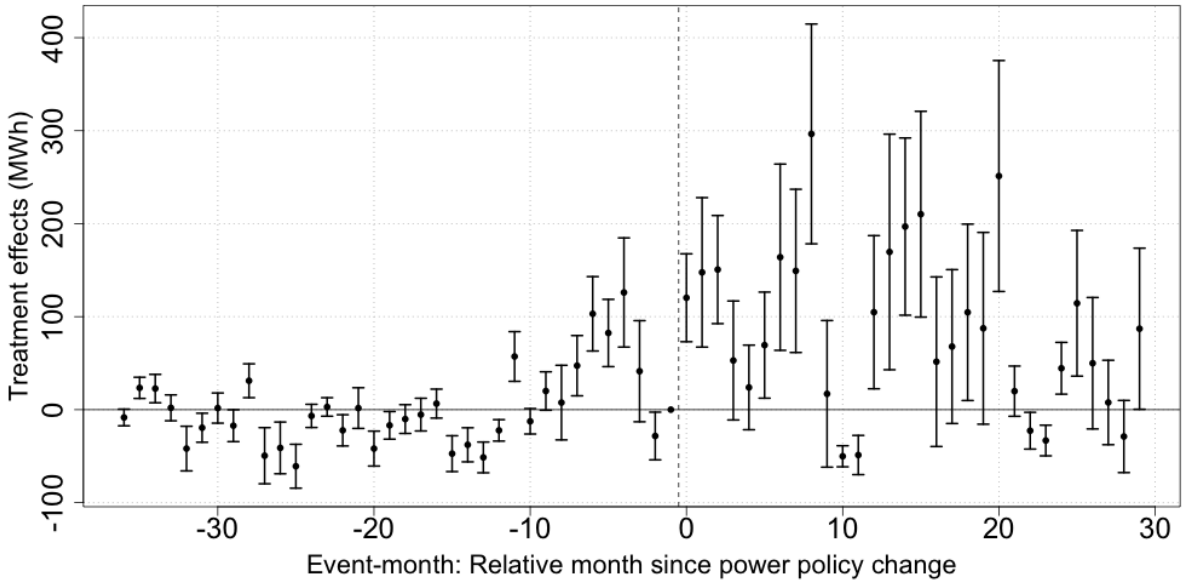
Notes: Agricultural power consumption in Telangana boundary districts is compared with that in Karnataka-Telangana boundary districts in Karnataka to evaluate the impact of the power policy. We estimate the coefficients specified in equation 2.1 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include district and time fixed effects. We cluster at the district level. The baseline mean agricultural power consumption in Telangana is 114.3 MWh. The dataset comprises 13 districts and 858 observations.

Figure 2.16. Impact on agricultural power consumption (Telangana vs Maharashtra)



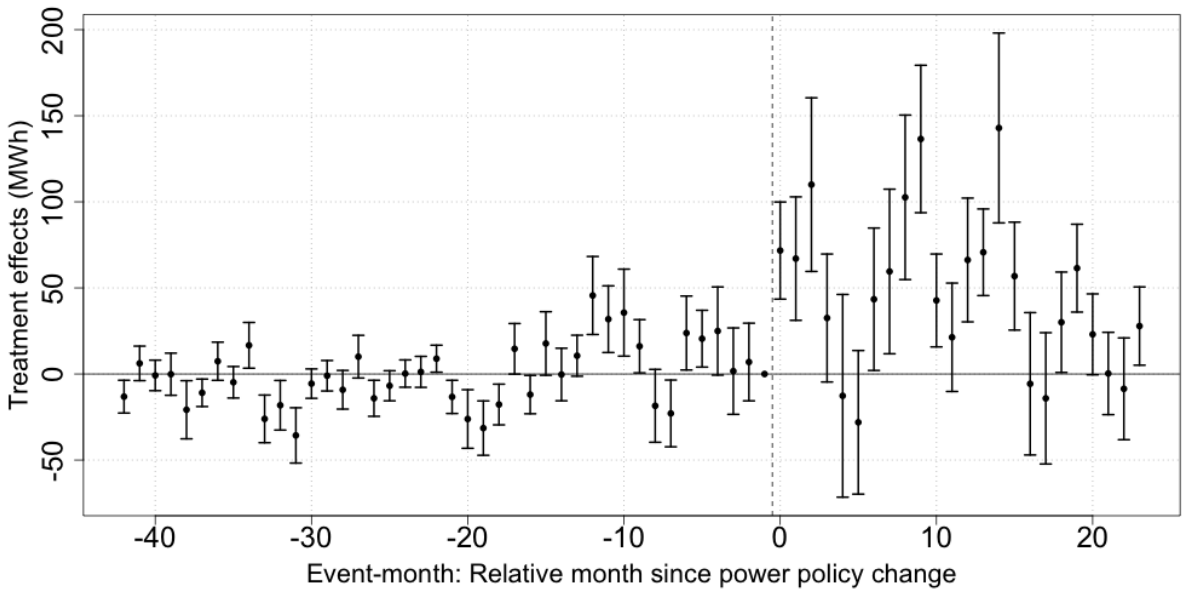
Notes: Agricultural power consumption in Telangana boundary districts is compared with that in Maharashtra-Telangana boundary districts in Maharashtra to evaluate the impact of the power policy. We estimate the coefficients specified in equation 2.1 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include district and time fixed effects. We cluster at the district level. The baseline mean agricultural power consumption in Telangana is 114.3 MWh. The dataset comprises 13 districts and 858 observations.

Figure 2.17. Impact on agricultural power consumption (Early treated districts in Telangana vs non-Telangana districts)



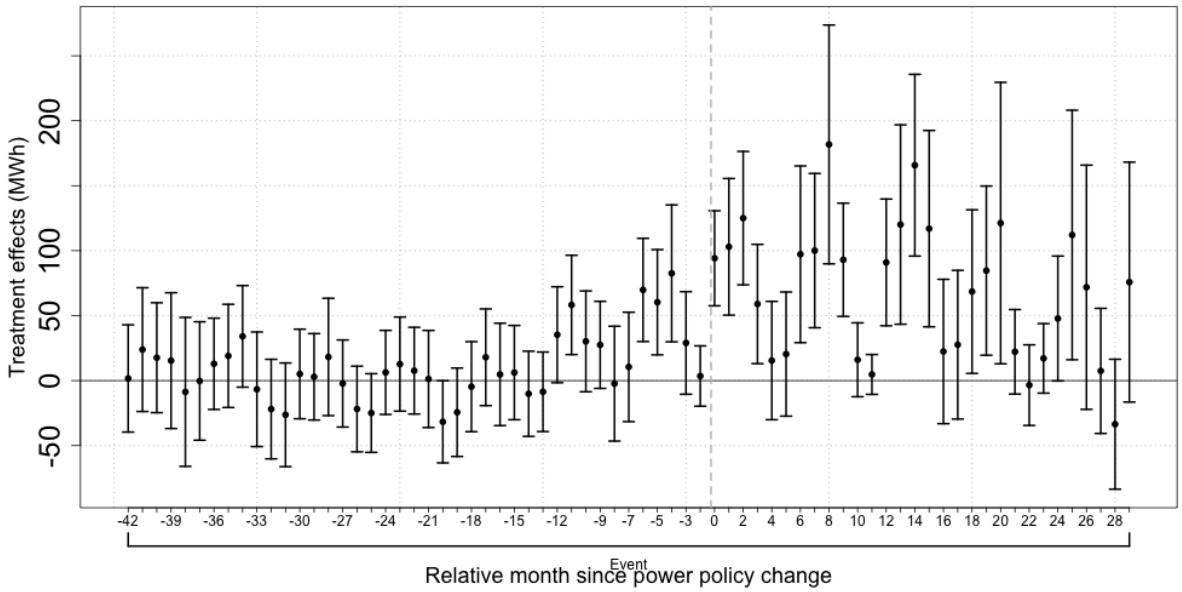
Notes: Agricultural power consumption in early treated Telangana boundary districts is compared with that in non-Telangana boundary districts to evaluate the impact of the power policy. We estimate the coefficients specified in equation 2.1 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include district and time fixed effects. We cluster at the district level. The dataset comprises 1122 observations.

Figure 2.18. Impact on agricultural power consumption (Late treated districts in Telangana vs non-Telangana districts)



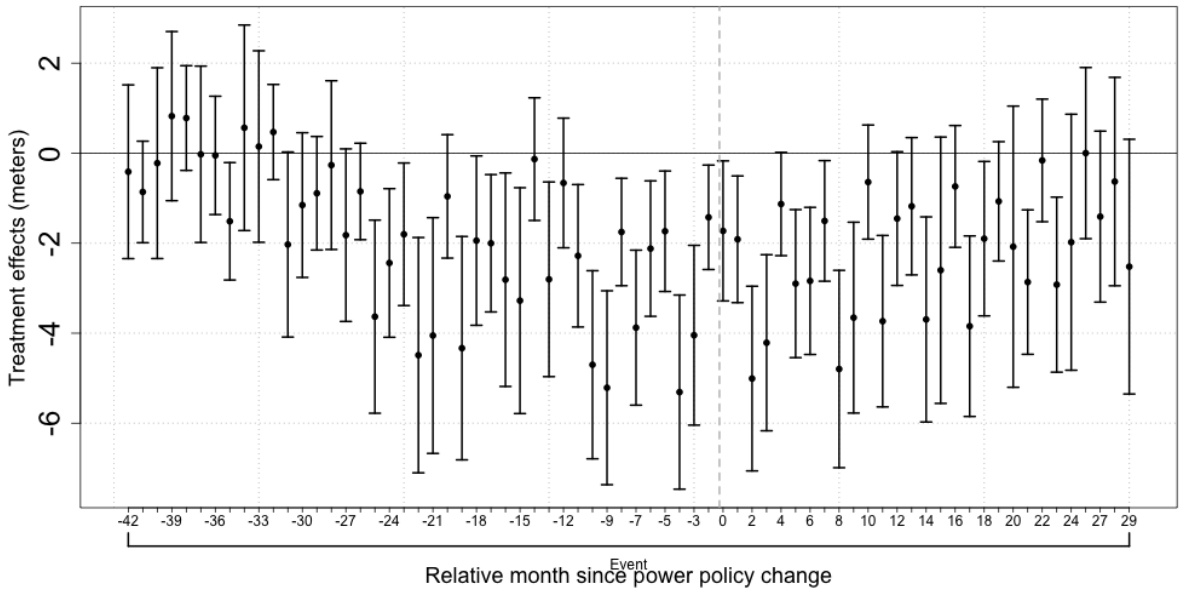
Notes: Agricultural power consumption in late treated Telangana boundary districts is compared with that in non-Telangana boundary districts to evaluate the impact of the power policy. We estimate the coefficients specified in equation 2.1 following (Gardner, 2022). All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include district and time fixed effects. We cluster at the district level. The dataset comprises 1320 observations.

Figure 2.19. Impact on agricultural power consumption using the OLS method



Notes: Agricultural power consumption in Telangana boundary districts is compared with that in non-Telangana boundary districts to evaluate the impact of the power policy. We estimate the coefficients specified in equation 2.1 using the OLS method. All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include district and time fixed effects. We cluster at the district level. The baseline mean agricultural power consumption in Telangana is 114.3 MWh. The dataset comprises 23 districts and 1,518 observations.

Figure 2.20. Impact on groundwater depth using the OLS method



Notes: Groundwater depth within 5 to 32.18 km of the boundary in Telangana is compared with that in non-Telangana states to assess the impact of the power policy. We estimate the coefficients specified in equation 2.2 using the OLS method. All coefficients are measured relative to event-month -1. The error bars represent 95% confidence intervals. We control for precipitation, temperature, and their six lags. We include segment and time fixed effects. We cluster at the well level. The baseline mean groundwater depth in Telangana is 9.25 meters below ground level. The dataset comprises 1585 wells and 30211 observations.

Repeated Geographic Regression Discontinuity models

As our analysis on groundwater depth involves spatial data, the threshold we use takes the form of a two-dimensional curve rather than a single point. This presents a challenge, as two wells situated close to the Telangana boundary may be far apart from each other spatially and therefore exhibit significant variation in unobserved characteristics. This can introduce bias if wells are not evenly distributed along the boundary. This problem does not arise in traditional one-dimensional RDDs. To address this issue, we leverage the spatial nature of our data and partition the long Telangana boundary into segments. By utilising segment fixed effects, we can exploit the variation in wells within each segment area and compare wells in close proximity that share similar characteristics, such as aquifer type, access to road and market, altitude, land type, proximity to surface water bodies, and so on. We fit a local linear regression model separately for each month t ranging from

July 2014 to December 2019.[13]

$$Y_{is} = \beta d_{is} + \tau D_{is} + \alpha_s + \delta X_{is} + e_{is} \tag{2.3}$$

where, Y_{is} denotes the groundwater depth at well i and segment s, measured in meters below ground level. In addition to the boundary segmentation that we do, the creation of distance from the boundary is another distinguishing feature of our geographical regression discontinuity analysis. In a geographic context, the threshold is a curve in two dimensions. To convert this two-dimensional threshold into a one-dimensional cutoff, we use the distance variable, denoted by d_{is}, which measures the distance from well i to the nearest boundary segment. This distance is positive for Telangana wells and negative for wells in the other three non-Telangana states. This is the running variable in traditional regression discontinuity methods. To avoid noisy estimates caused by overfitting of groundwater depth observations (Gelman and Imbens, 2019), we use a linear distance variable. D_{is} is an indicator variable which takes a value of 1 for Telangana wells and 0 for non-Telangana wells. α_s are the segment fixed effects, which enable us to compare wells within a segment area that are closer in nature. X_{is} represents control variables, including precipitation, temperature, and their six lags. We use an MSE optimal bandwidth around the cutoff, which is chosen to be inversely proportional to the fourth root of the number of observations in the data (Calonico and Sebastian, 2021). We use a triangular kernel, which assigns higher weights to wells near the boundary and weights that decrease linearly as we move away from the boundary. We run the same specification for early treated districts from July 2017 to December 2017 to get the coefficients of early treatment dummy. We also check for robustness with rectangular kernel that assigns uniform weight.

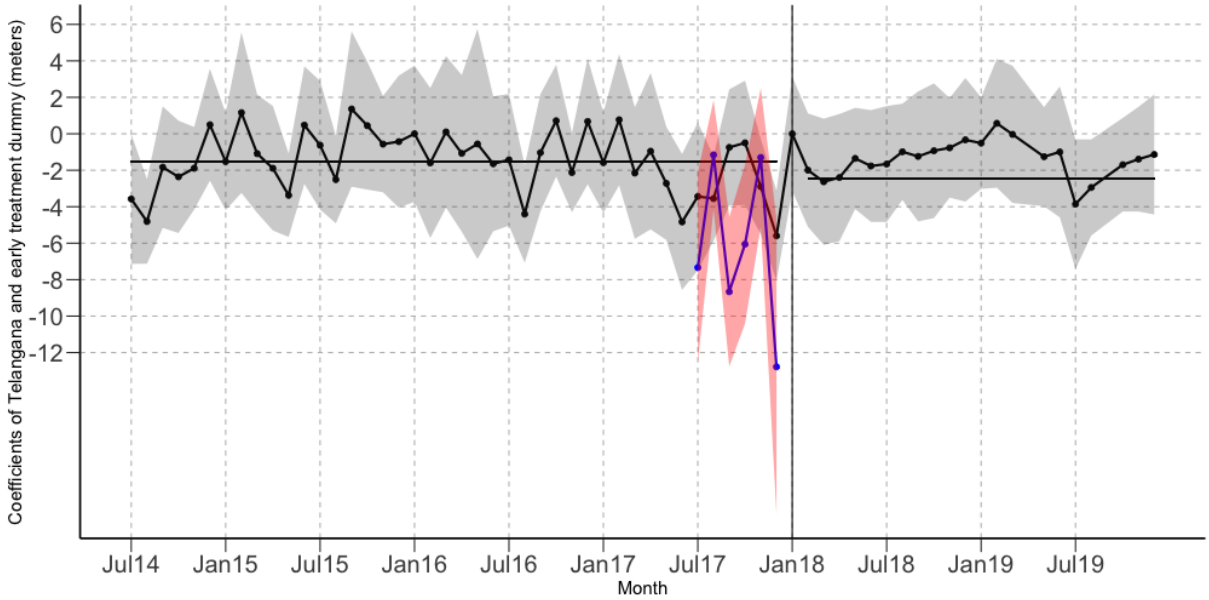
The estimated difference between the monthly groundwater depth in Telangana and neighboring states (the coefficients on the Telangana and early treatment dummies using the monthly Geographic Regression Discontinuity from equation 2.3) is shown in Figure 2.21. All monthly coefficients are shown relative to January 2018. Almost all the monthly

[13]It is worth noting that we use a crossesectional model in this specification, as the robust estimation technique of Calonico, Cattaneo, Titiunik, and others are only applicable to cross-sectional data (Calonico and Sebastian, 2021).

coefficients are insignificant and they show roughly a constant trend. The average effect of the policy is calculated using post-policy minus pre-policy mean of the coefficients, accounting for the variance-covariance matrix. This results in a value of -0.39 meters with a standard error of 0.47, which is statistically insignificant. This estimate is consistent with the visual intuition in Figure 2.21. The unrestricted power policy appears to have had no effect on the groundwater depth in Telangana.

The bandwidths for each month range from 25 km to 46 km, with a mean of 32.18 km.

Figure 2.21. Repeated Geographic Regression Discontinuity model estimates of the impact on groundwater depth

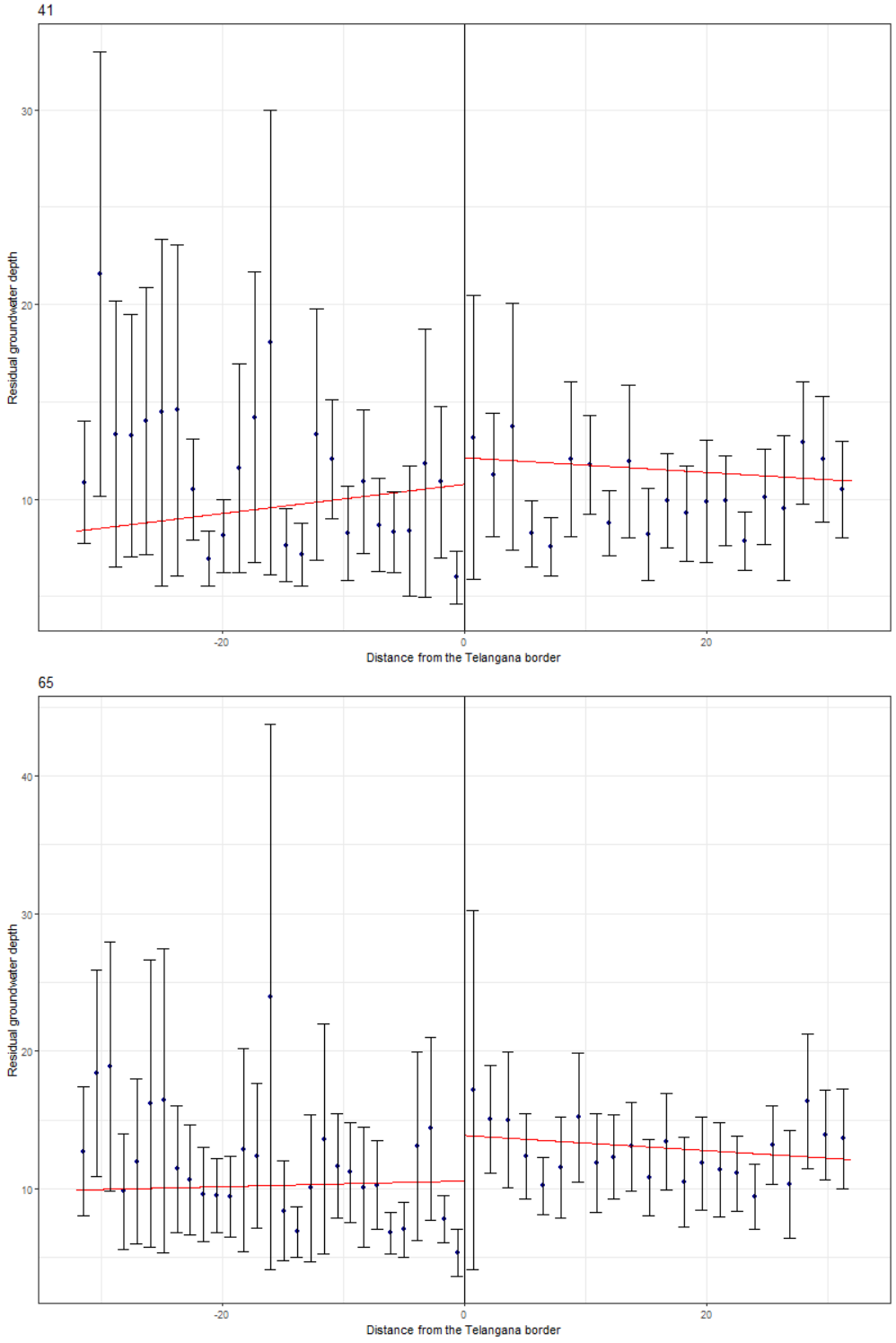


Notes: Groundwater depth in Telangana is compared to non-Telangana states to evaluate the policy's impact. The coefficients of the Telangana dummy (in black) indicate the pseudo treatment effect from July 2014 to December 2017 and the treatment effect of the policy from January 2018 to December 2019. Additionally, the coefficients of the early treatment dummy (in blue) indicate the treatment effect for early-treated districts in Telangana from July 2017 to December 2017. The corresponding 95 % confidence intervals are shaded. We estimate these coefficients for each month using the Repeated Geographic Regression Discontinuity model as specified in equation 2.3. We use a triangular kernel. We control for precipitation, temperature, and their six lags. The bandwidths for each month range from 25 km to 46 km, with a mean of 32.18 km. The effective number of wells/observations for each month range from 229 to 934, with a mean of 552.

We show regression discontinuity plots for a pre-monsoon and a post-monsoon month in Figure 2.22 using equation 2.3. Residual groundwater depth (controlling for precipitation and temperature and their six lags) increases slightly as we move from non-Telangana to Telangana side for both the months, May 2017 (pre-policy) and May

2019 (post-policy). We observe roughly similar patterns for all other months.

Figure 2.22. Regression discontinuity plots for pre-monsoon months, May 2017 (pre-policy) and May 2019 (post-policy) respectively



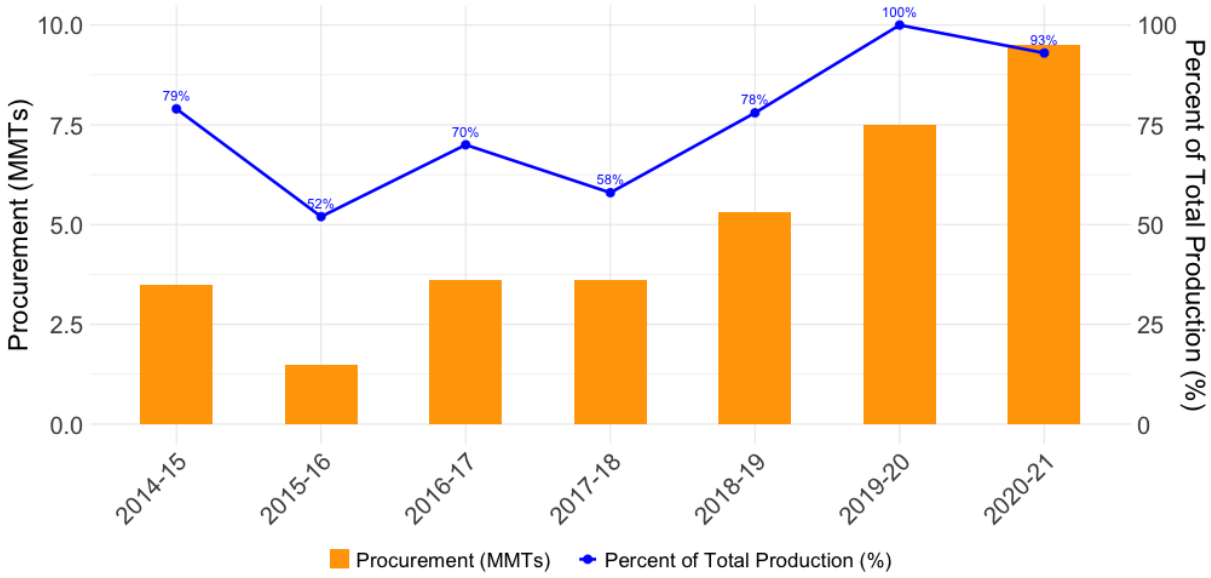
Notes: We use Repeated Geographic Regression Discontinuity model as specified in equation 2.3 for months 41 (May 2017) and 65(May 2019). Bins (dots) are based on mimicking variance evenly-spaced method using spacings estimators. Error bars show 95 % confidence intervals. We use a triangular kernel. Bandwidth is chosen optimally. We control for precipitation, temperature, and their six lags to get residual groundwater depth.

Figure 2.23. Share of different types of wells in Telangana

Key Parameters of 6th MI Census-Telangana				
Parameter		**Unit**	**Value**	**%**
Number of schemes	Dugwells	No.	4,57,784	27.25
	Shallow Tubewell	No.	76,790	4.57
	Medium Tubewell	No.	6,77,156	40.31
	Deep Tubewells	No.	3,67,519	21.88
	Ground Water schemes	No.	15,79,249	94.01
	Surface Flow	No.	62,753	3.74
	Surface Lift	No.	37,866	2.25
	Surface Water schemes	No.	1,00,619	5.99
	Total schemes	No.	16,79,868	100.00

Source: 6th Minor Irrigation Census conducted between 2017 and 2019

Figure 2.24. Annual rice procurement



Notes: The year 2014-15 refers to the period from July 2014 to June 2015.

Source: Saini, Khatri, and Kumari (2023), various issues of the Food Grain Bulletin (DFPD)

Figure 2.25. Groundwater flow diagram showing discontinuous aquifer in pre-monsoon period

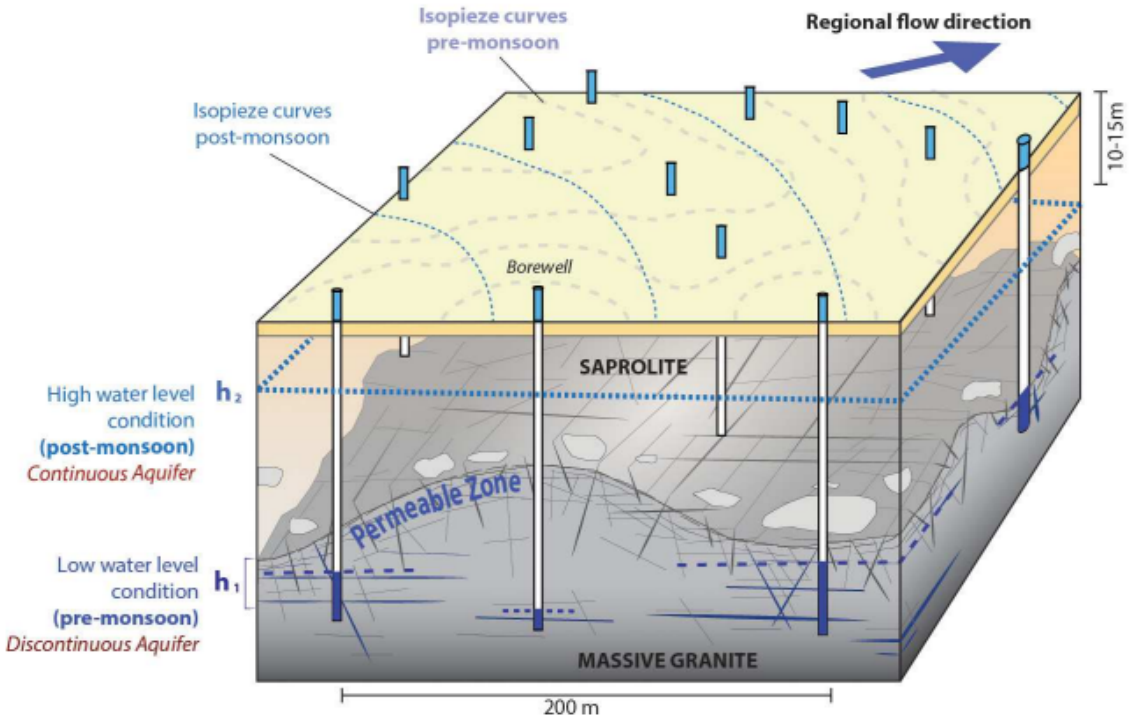
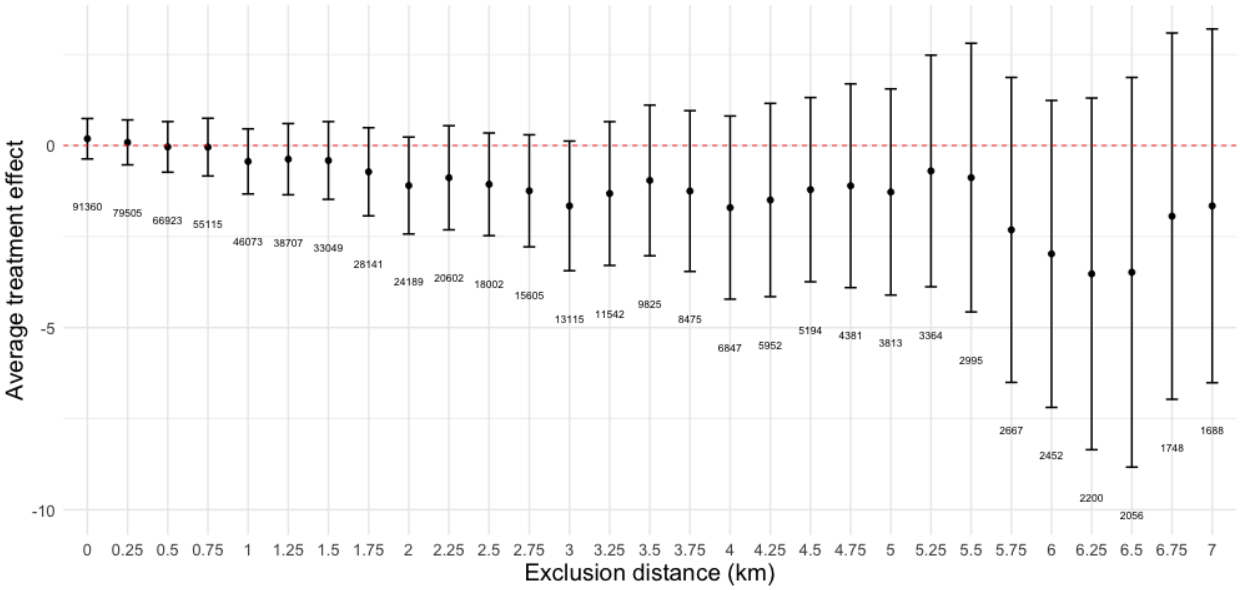


Fig. 8. Schematic conceptual model of groundwater flow at watershed scale (modified from Guihéneuf et al. 2014).

Source: Maréchal et al., 2018

Figure 2.26. Effect of the power policy on groundwater depth in monitoring wells located at least x km away from the nearest surface water body for various values of x.



Notes: We estimate the average treatment effect of the power policy using a staggered DiD approach, following Gardner (2022). We control for precipitation, temperature, and their six lags. We restrict our sample to observations from January 2016 onwards, closer to the treatment month, where the pre-trend is stable. We use all wells from boundary districts instead of only those within 5–32 km of the boundary to ensure a sufficient number of observations at higher distance cut-offs. We include segment and time fixed effects. We cluster at the well level. The error bars represent 95% confidence intervals. The number of observations is indicated below the error bars. There are 5802 wells at the 0 km cut-off, 1567 at the 2 km cut-off, 229 at the 5 km cut-off, and 84 at the 7 km cut-off.

Figure 2.27. Heterogeneity of hard rock aquifers in boundary state Karnataka

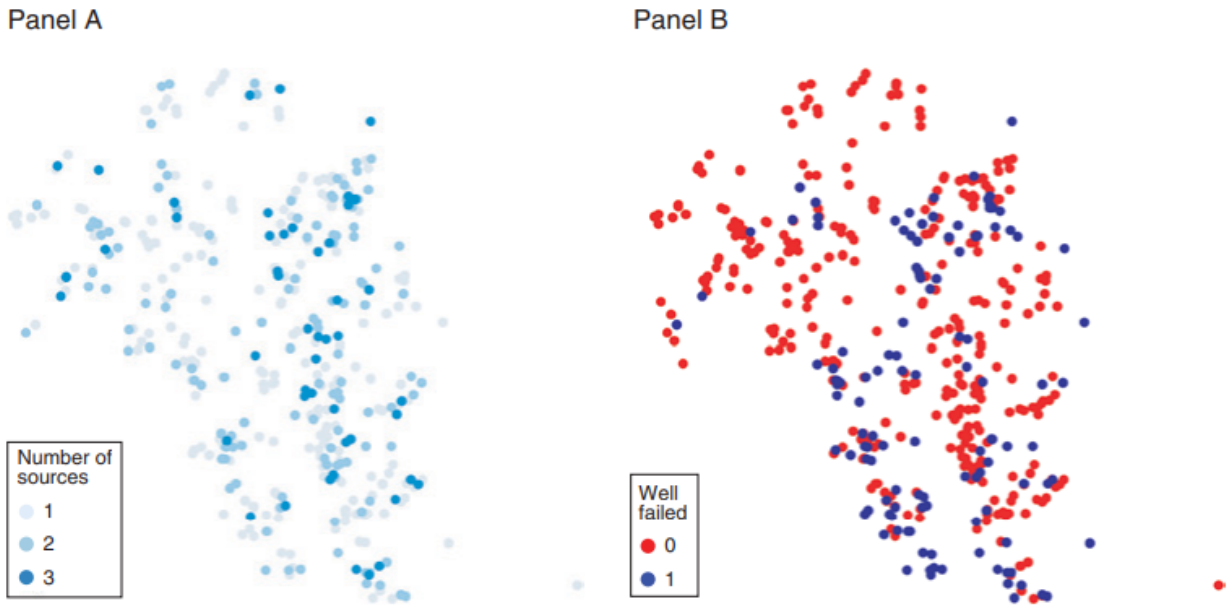
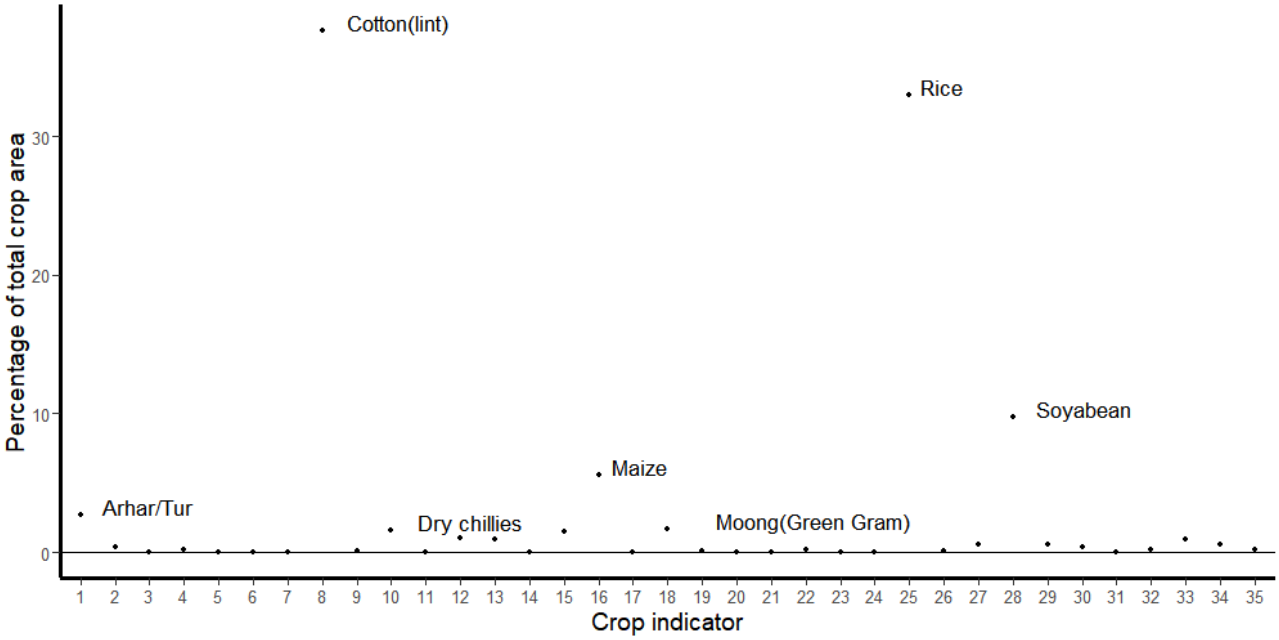


FIGURE 3. HYDROGEOLOGICAL DATA

Notes: Plot of the number of water sources intercepted by each well, panel A, and borewell status (active, in blue/ failed, in red), panel B, from a complete census of all borewells in a cluster of villages in the study area. The horizontal scale of the plot is about 5 km.

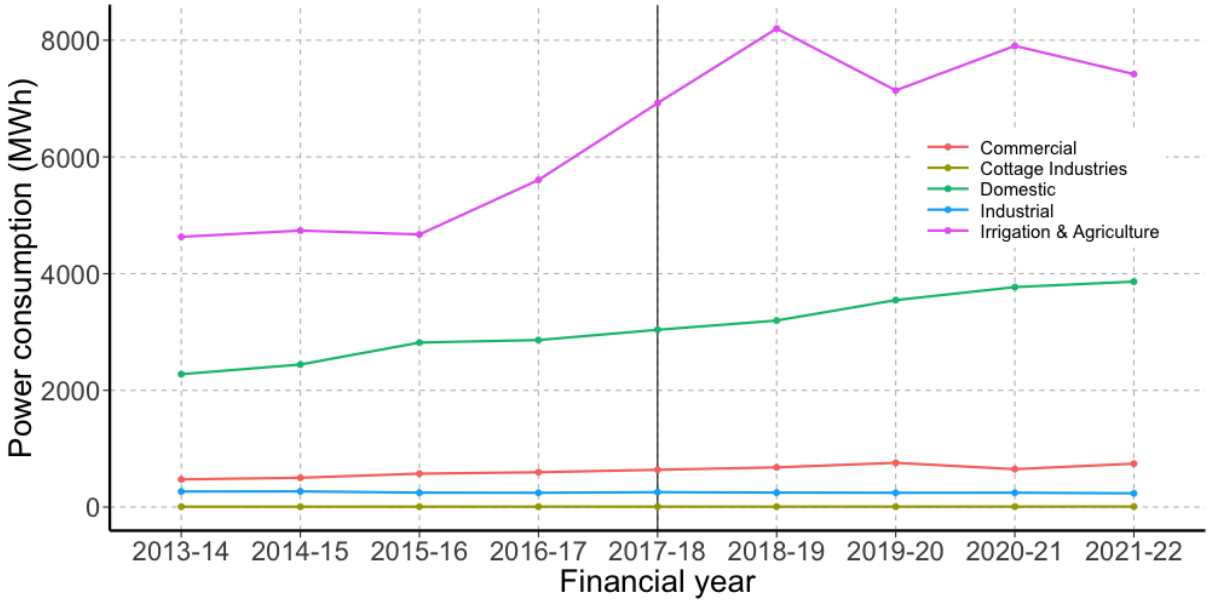
Source: Blakeslee, Fishman, and Srinivasan, 2020

Figure 2.28. Major crops in Telangana boundary districts, 2014-15.



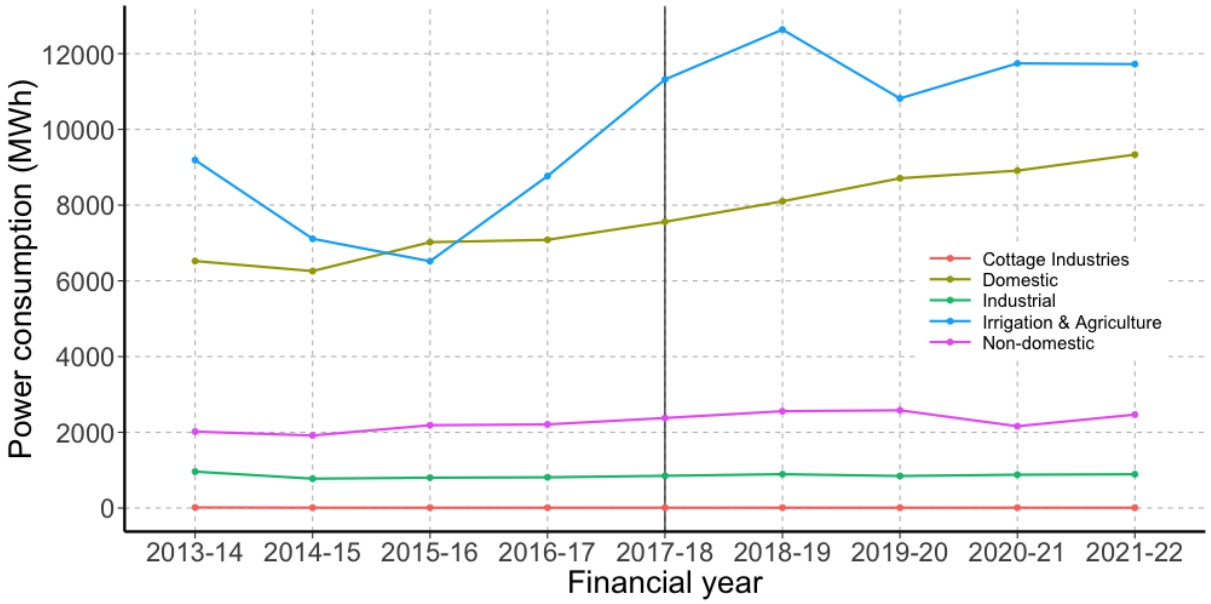
Notes: Based on data from Directorate of Economics & Statistics, Ministry of Agriculture, Government of India.

Figure 2.29. North Telangana annual power consumption by sector



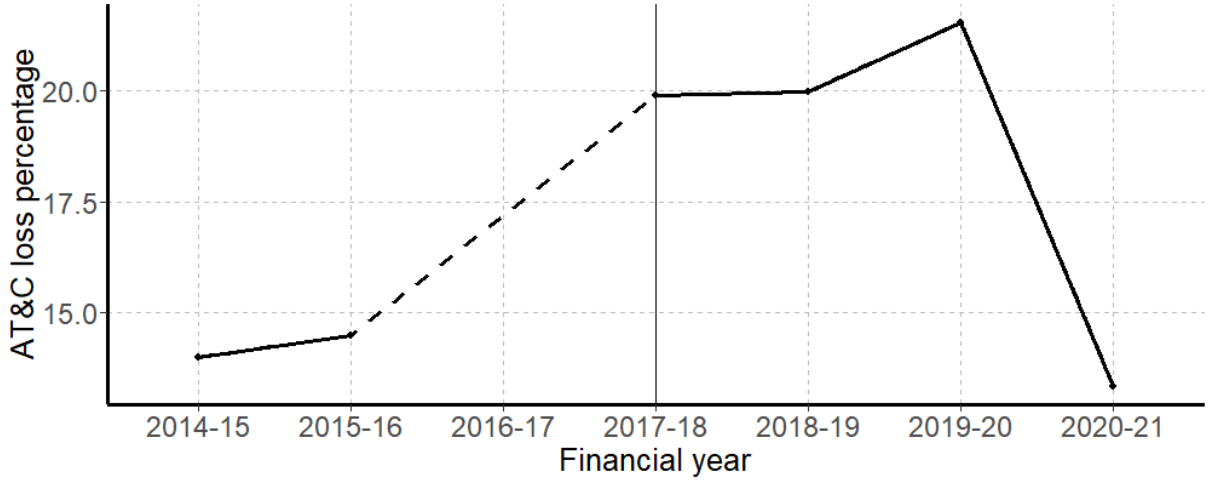
Notes: Based on annual reports from North Telangana Power Distribution Company. The financial year is from 1 April to 31 March. Vertical line denotes the financial year during the policy.

Figure 2.30. South Telangana annual power consumption by sector



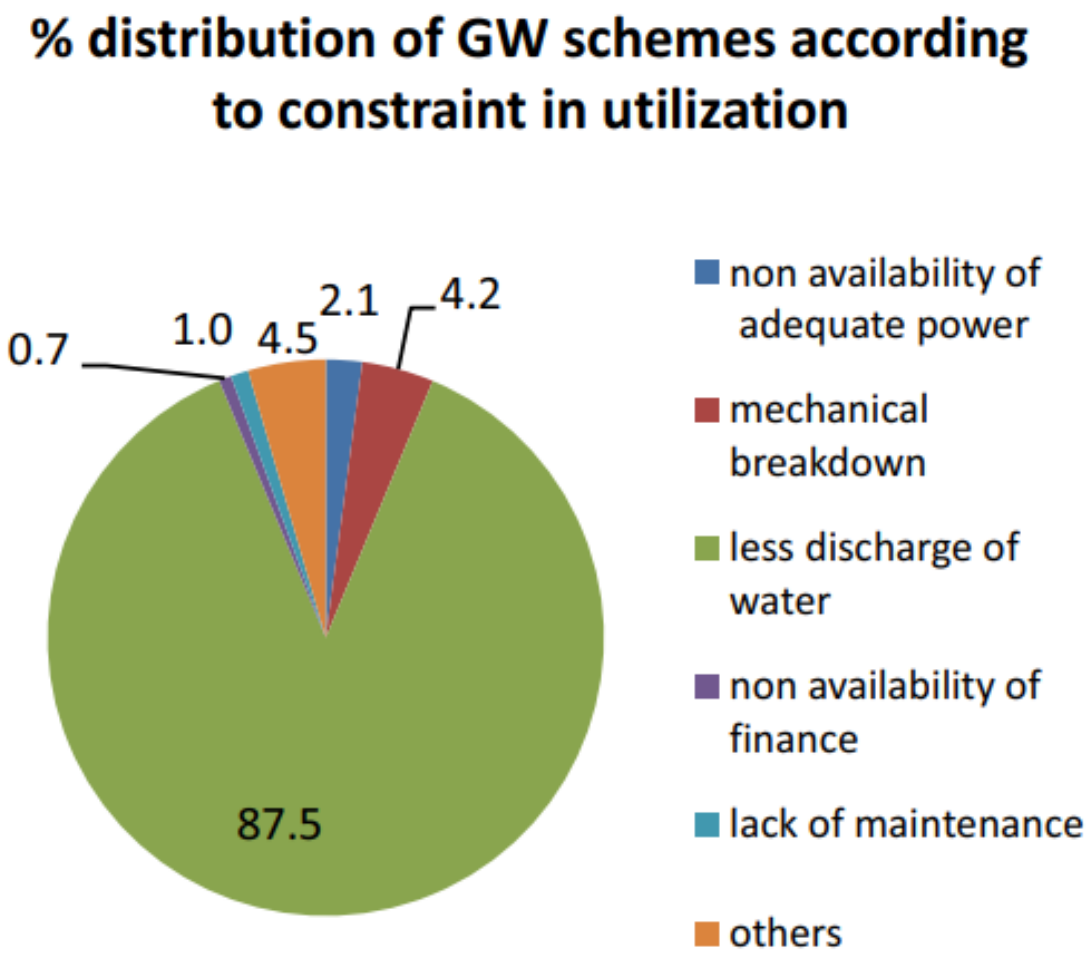
Notes: Based on annual reports from South Telangana Power Distribution Company. The financial year is from 1 April to 31 March. Vertical line denotes the financial year during the policy.

Figure 2.31. Annual aggregate technical and commercial loss



Notes: Based on the report on the performance of Power Utilities by the Power Finance Corporation Of India. The financial year is from 1 April to 31 March. Vertical line denotes the financial year during the policy.

Figure 2.32. Underutilisation of farmer wells



Notes: 71,219 wells (16.77%) are under-utilised in Telangana according to the 6th Minor Irrigation Census (2017-19). The figure shows reasons for this under utilisation.

Figure 2.33. Anecdotal report on underutilisation of farmer wells in The News Minute

Rajesh Serupally

It was a busy election campaigning day in Cheriyal Mandal of Siddipet district. Harish Rao who was the ex-irrigation Minister of Telangana is the elected MLA from Siddipet. The air was filled with the cackle of speeches being played from PR vans of each of the various parties. As we skip the main roads and travel into the villages and try and follow the zig-zagging mud roads that lead to the farms, that is when you notice a strange noise, a continuous roar, clearly audible over the cacophony of the speeches. Any new person is bound to find this noise jarring, and we were no different. It strangely made us quite tense, uneasy and uncomfortable. As we walked towards the sound, we realised to our surprise that it is the sound of the tens of bore well motors in the area that are the source of this awful din.

Intrigued by this unusual sound apparently made by the motors, we decided to ask Mallesh, a young farmer, about it. His family owns four acres of land where the groundwater dried up this year. "Since we have 24 hours of power supply, we just allow the motor to run round the clock with the hope that at least some of the time we may get water," he explains.

Chapter 3

Effects of a Transition from LPG to Induction cookstoves in Kerala Anganwadis, India

3.1 Introduction

Globally, there has been significant progress in electrification over the past decade. The number of unelectrified people decreased from 1.1 billion in 2010 to 685.2 million in 2022. In the same year, about 2.1 billion people, roughly one-third of the global population, lacked access to clean cooking facilities (*Tracking SDG7: The Energy Progress Report* 2024). In the context of India, the entire population now has access to electricity. [1] But, half of the Indian households continue to rely on firewood for cooking (Mani et al., 2021) and only 5% of Indian households use any electric cooking appliance as per India Residential Energy Survey 2020 (Agrawal et al., 2021). While the use of clean fuels like LPG for cooking has increased (71% of households primarily use LPG, according to India Residential Energy Survey 2020), electric cooking could offer a more sustainable long-term alternative, especially as renewable electricity becomes more affordable. The existing gap between electrification and the adoption of electric cooking presents an opportunity for electric cooking to emerge as a clean and scalable solution, particularly given the significant health and environmental costs associated with biomass and, to a lesser extent, gas cooking.

The residential biomass fuel usage for cooking and heating in India is one of the primary contributors to ambient PM2.5 levels, a concerning finding by Venkataraman et al. (2018). The severity of the issue is underscored by significant spikes in PM2.5

[1] India achieved the milestone of 100% electrification in its villages in April 2018 (*Executive Summary on Power Sector* Mar-2024). According to the Government of India, all the States have reported 100% electrification of all the willing un-electrified households under the Saubhagya scheme by March 2021.

concentrations within kitchens during cooking hours, occasionally exceeding 1000 $\mu g/m^3$ with solid fuels (Somanathan et al., 2022). Another study by Arora et al. (2020) shows that the mean cooking time concentrations of PM2.5, PM1 and CO measured were $616.8 \pm 405.6\,\mu g/m^3$, $525.4 \pm 359.7\,\mu g/m^3$ and 16.7 ± 17.4 ppm respectively with traditional cookstoves. Exposure to household air pollution leads to noncommunicable diseases such as stroke, ischemic heart disease, chronic obstructive pulmonary disease (COPD), childhood pneumonia, asthma, lung cancer, among others (Balmes, 2019; Schraufnagel et al., 2019); and according to WHO (2023), household air pollution was responsible for an estimated 3.2 million deaths annually in 2020, including over 237,000 deaths of children under the age of 5. Women and children, often responsible for cooking and collecting firewood, bear the greatest health burden from the use of polluting fuels and technologies in homes (Maes and Verbist, 2012). A study by Yu et al. (2021) using a Chinese national survey of about 17,000 residents aged over 45, showed that consistent use of solid fuels was associated with shorter sleep duration and higher frequencies of feeling unrested compared with cleaner fuels. These findings underscore the urgent need for cleaner and more efficient cooking solutions to mitigate the adverse health and environmental impacts associated with traditional cooking practices, where electric cooking can be another clean cooking solution.

Cooking with LPG (gas) generally has an energy efficiency of around 50% (Shen et al., 2018). In comparison, induction cookstoves, which employ electromagnetic induction to heat cookware directly if it's ferromagnetic, can reach efficiencies up to 90%, higher than the 60% to 75% efficiency observed in traditional electric coil stoves (Gould et al., 2023).[2] Further, gas cooking is linked to an increase in indoor air pollutants such as nitrogen dioxide (NO2), which are associated with harmful health effects (Kephart et al., 2021). Induction cookstoves are one of the major electric cooking option among others. Induction cookstove use instrumented by electricity availability reduced PM2.5 in kitchens by 200-450 $\mu g/m^3$ during cooking hours (Somanathan et al., 2022). In an another study, induction cookstove reduced mean 24 h PM2.5 and PM1 concentrations by 72% and 74%,

[2]Efficency of these cookstoves are sensitive to the test environment.

respectively, and nearly 100% of CO (Arora et al., 2020).

One of the major barriers to the adoption of clean cooking is the cost. Induction cookstoves have become relatively cheap to buy and operate (Somanathan et al., 2022). Further, part of the one time cost can be subsidized by the government or the other organisations for economically disadvantaged groups. The Government of India has already announced distribution of 2 million induction cookstoves in November 2023. Variable cost becomes important in such a scenario for sustained use. However, limited studies have been conducted to inform on their variable cost and fuel consumption, with most of the studies confined to reports and laboratory settings. These costs are non-uniform and depend on local tariffs across all states of India. A report by ESMAP (2020) compares the current and projected costs of various electric cooking solutions (e.g., electric pressure cookers, rice cookers, hot plates, induction cookstoves, infrared stoves) with the costs of widely-used fuels for cooking across five case studies in Kenya, Zambia, Myanmar, and Tanzania, shows that electric cooking on national grids or mini-/micro-hydropower is already cost-effective for many people. Based on aggregated data from multiple African and Asian countries, including India, a study by Scott and Leach (2023) found that the cost of cooking with an electric pressure cooker (EPC) is approximately one third of the cost of using LPG and less than 20% of the cost of using charcoal and compared to resistive element hotplates, modern hobs (induction and infrared) can save 10%, automated devices like rice cookers can save approximately 25%, and EPCs can save around 50%. A transition program in Ecuador led to over 750,000 households switching from gas to induction cookstoves, resulting in a 5% increase in total residential electricity consumption between 2015 and 2021, alongside a decrease in LPG sales, greenhouse gas emissions, and both all-cause and respiratory-related hospital admissions (Gould et al., 2023). Furthermore, a study by Roy (2024) shows that while the fixed cost of switching from solid fuels to LPG or electricity is almost similar, the annual variable costs for households are lower with electricity. Similarly, cooking with the induction cookstove has a lower energy cost compared to cooking with the unsubsidised 12 kg LPG cylinder in Indonesia (Irsyad et al., 2022). Jain, Choudhury, and Ganesan (2015) have shown that the Levelised Cost of Energy (that includes capital,

operational and maintenance cost, the cost of financing and depreciation of assets) of induction cookstoves is lower than that of LPG. We look at this variable cost component and other outcomes of a transition from gas to induction cookstoves in a practical empirical setting. Households may hesitate to adopt electric cooking due to the costs of induction cookstoves and compatible utensils, as well as increased electricity bills. We look at a framework where these constraints are relaxed.

There have been multiple growing studies on determinants of clean cooking since 2015 onwards (Guta et al., 2022), but studies on determinants of electricity as fuel is limited. Feyisa (2019) looks at determinants of household adoption of electric injera mitad in Urban Ethiopia. Pattanayak et al. (2019) in their multiphase long term study looks at various supply and demand side factors that determine the adoption of electric coil stove and improved biomass stove. Existing research on electric cooking adoption largely focuses on households and pays limited attention to induction cookstoves, which are currently the most widely used electric cooking appliance in India. This study, by contrast, examines day-run institution—anganwadis—that is well-suited for electric cooking using solar power, since they operate during daylight hours and storing solar energy for later use is costly. The study also focuses explicitly on the use of induction cookstoves in these settings.

We follow a difference-in-differences method within an institutional framework where, unlike households, the meals are fixed (three times a day), and the weekly dishes are fixed. This setup ensures that outcomes are not influenced by household socioeconomic factors and behaviors. Additionally, we have detailed knowledge about non-cooking days (vacation days) and the number of children for whom food is cooked. This controlled environment allows for a more accurate assessment of the impacts of electric cooking adoption. We use monthly administrative data from Anganwadis (public child care centres) in Kerala to perform the monthly analysis to evaluate the change in costs and consumption of gas. Additionally, we use pre- and post-intervention survey data to look at the change in gas consumption and total cooking time post-intervention. Using survey data, we examine the adoption rate of a new technology, specifically induction cookstoves, when the upfront cost is fully subsidized. Additionally, we analyse the benefits and barriers associated with

using induction cookstoves and explore the reasons behind their non-adoption.

We find that there is a decrease in LPG consumption by at least 10 % for the treatment group post-intervention, compared to the baseline average, using both administrative and survey data. We find a corresponding increasse in electricity consumption using administrative data. Our findings show that Anganwadis are saving roughly 300 INR per month on average, by partially adopting induction cookstoves. Although the total cooking time showed a decrease post-intervention based on survey data, this reduction was not statistically significant. Additionally, we observed that induction cookstove adoption was not universal even though the upfront cost was fully subsidized. Most induction cookstove users reported that induction cookstoves were time-saving, allowing teachers and helpers more time with children, that they were convenient, cheaper than gas, safe, and tidy. Non-adoption was primarily driven by lack of electricity infrastructure, such as inadequate switchboards and wiring issues.

The structure of the paper is as follows: Section 2 describes the background. Section 3 describes the administrative and survey data. Section 4 describes the identification and estimation methods, results on LPG consumption, total cooking time, adoption rate over time, enablers and barriers to adoption, and reasons for both non-adoption and discontinued adoption. Section 5 concludes with policy implications.

3.2 Background

Energy Management Centre (EMC) is an autonomous organisation under the Department of Power, Government of Kerala. EMC works on comprehensive and multi-disciplinary institutional objectives encompassing all aspects of energy, with a focus on energy-environment-development interactions. Under the Integrated Child Development Services (ICDS) Scheme, the EMC proposed the Angan Jyothi project, aiming to enhance the energy efficiency of Anganwadis.

ICDS is a flagship program of the Government of India dedicated to providing early childhood care and developmental programs for children and nursing mothers, recognized

as one of the world's largest initiatives of its kind. Anganwadis (day care centres) are the focal points for delivering ICDS services in India. These Anganwadis are run by a female worker (popularly called teachers) and a female helper. They play a crucial role in implementing the ICDS program by providing supplementary nutrition to children, pregnant women, and lactating mothers; conducting pre-school activities for children aged 3-6 years; regularly monitoring health and nutrition; facilitating immunizations; educating mothers and the community on health, hygiene, and nutrition; and offering referral services for medical attention when needed. All expenses related to Anganwadis are fully covered by the government.

The Angan Jyothi project aims to eventually equip all 33,115 Anganwadis in Kerala with various energy-efficient technologies namely electric induction cookstoves, induction-compatible utensils (Pressure Cooker, Milk Boiler with lid, Idly Cooker with lid, Uruli with lid, Sauce pan with lid, Rice pot with lid), hotboxes, Brushless Direct Current (BLDC) fans, LED lights, grid connected solar photovoltaic system (2 kW), ensuring swift cooking processes. One of the program's objectives is to cut 64,000 tons of carbon emissions by replacing LPG with energy-efficient electric induction cookstoves. It also targets substantial cost savings on LPG, for the government. The project seeks to ensure continuous energy availability through solar power and generate 60 MW of green power. Empowering women, particularly Anganwadi workers, through time-saving clean energy cooking is a priority. Ultimately, the program strives to turn Anganwadis into a grassroots-level energy efficiency demonstration center for an efficient and sustainable energy landscape in India.

It is a rolling project. In its pilot phase, 5 Anganwadis were treated, followed by 424 Anganwadis in Phase 1 across 20 panchayats in Kazhakoottam and Chittur constituencies (see Appendix Figure 3.5 for their locations).[3] Since induction cookstoves are a relatively new technology, many Anganwadi workers would have had little or no prior experience using them. Following the intervention, training sessions on the proper use of induction

[3]In the subsequent Phase 2, 85 panchayats (roughly 2000 Anganwadis) were treated as part of the Navakerala Karmapathidhi initiative of the Government of Kerala, launched for the socio-economic development of the state.

cookstoves were conducted in a workshop organized by EMC, which was attended by most Anganwadi workers.

In this paper, we study the Phase 1 intervention implemented in May and June 2023, where treated Anganwadis were given induction cookstoves along with compatible utensils, free of cost. Hotboxes, Brushless Direct Current (BLDC) fans, LED lights, and grid connected solar photovoltaic system (2 kW) were also given. But, they were given gradually and the installation happened in phases. Moreover, these are not related to our outcomes of interest, which are LPG consumption and total cooking time.

Anganwadis have an incentive to adopt induction cookstoves because they receive an additional hob for cooking. We hypothesize that this would lead to a reduction in LPG use, an increase in electricity consumption, and a decrease in total cooking time. We test these hypotheses using the data discussed in the following section.

3.3 Data

The Phase 1 treatment was done in Kazhakkoottam in May and June 2023, and in Chittur in May 2023. We selected control Anganwadis either from the same panchayat or from the neighbor panchayat in the same project office.[4] We collect administrative as well as survey data for 424 treatment and 258 control Anganwadis.

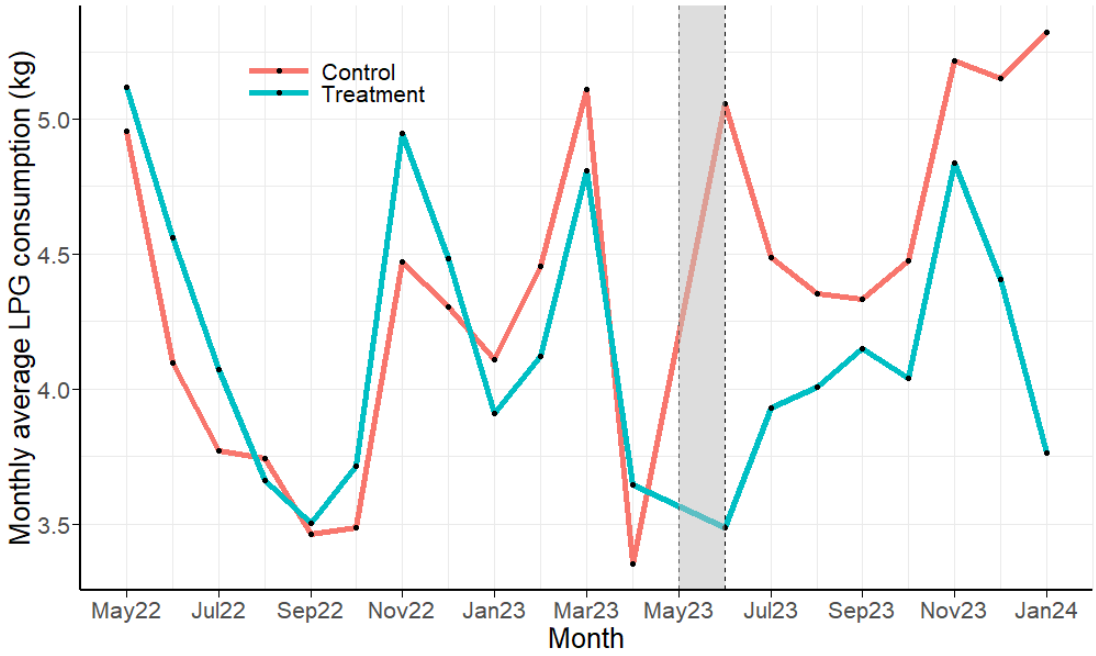
3.3.1 Administrative data

We collected monthly administrative data on LPG and condiments expenditure from May 2022 to February 2024. LPG cylinders are bought periodically, and usually lasts a few months. We refer to time between two purchases as a spell. Condiments expenditure was reimbursed by multiplying the total student attendance by 2 until October 2023, and by 5 from November 2023 onwards. So, we constructed total attendance in each month based on condiment expenditure data. Using the total attendance in each month as a weight for a spell, we calculated the monthly gas consumption (in kg) for each month for

[4]The administrative hierarchy follows this sequence: State, District, Constituencies, Block/Project offices, Panchayats, Anganwadis.

analysis. If we don't know how long a spell is, we exclude those monthly observations. If a spell overlaps with intervention months, we exclude those observations since they are a mix of treated and control observations. We include only those Anganwadis that have at least one pre-intervention and one post-intervention observation. Consequently, we lose many Anganwadis during this process. Finally, we have data on 110 treatment and 168 control Anganwadis, from May 2022 to February 2024. This administrative data includes gas consumption and the total attendance in each month, calculated as the sum of daily student attendance (in student-days). We show monthly gas consumption in Figure 3.1. There is a general decrease in the monthly average LPG consumption in the treatment group post-intervention compared to the control group.

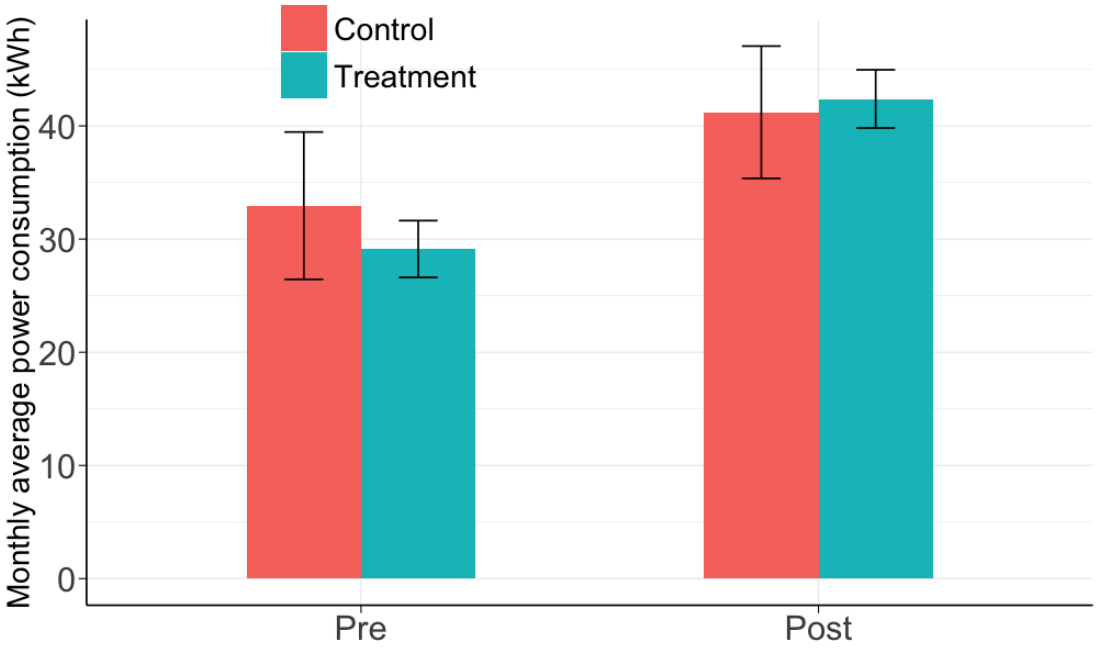
Figure 3.1. LPG consumption from monthly administrative data



Notes: Author's calculation based on monthly administrative data from Anganwadis. There are 110 treatment and 168 control Anganwadis with 3435 observations.

We requested monthly electricity data for these Anganwadis from April 2022 to October 2024. Monthly power consumption in treatment group is less than the treatment group in pre-intervention period, but post-intervention, there is a increase in monthly average power consumption (Figure 3.2). There is diff-in-diff increase in power consumption by 17-percent.

Figure 3.2. Power consumption from monthly electricity data



Notes: Author's calculation based on monthly electricity data. There are 241 treatment and 116 control Anganwadis with 5130 observations.

3.3.2 Survey data

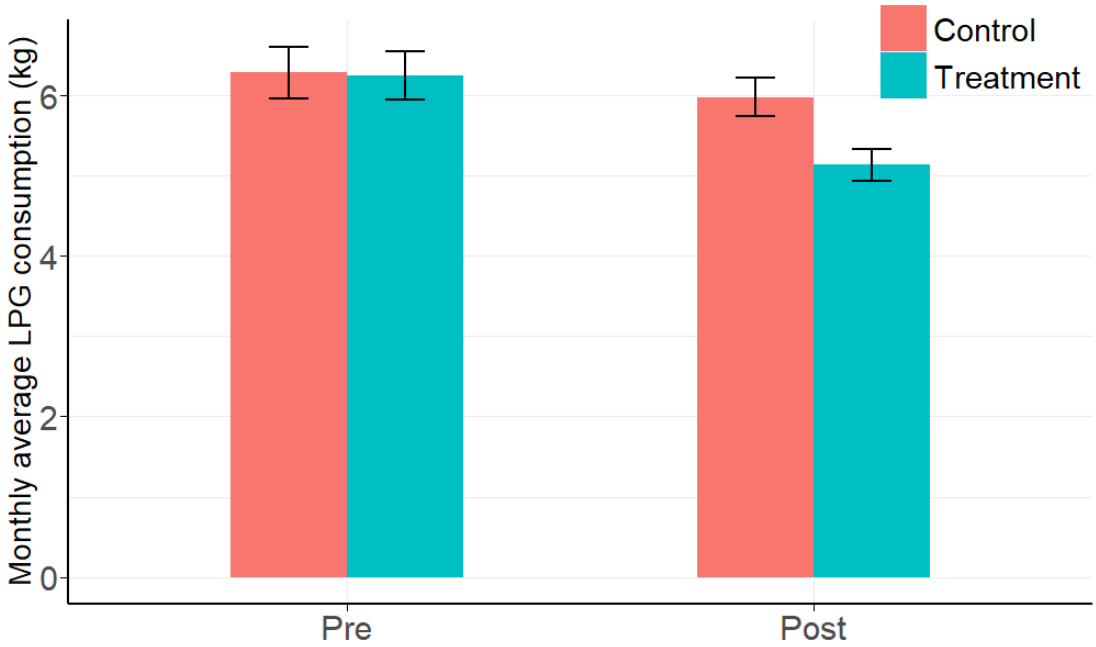
To better understand the pattern of gas consumption over time, we conducted both a baseline survey (May-July 2023) and an endline survey (Apr-June 2024) of Anganwadi teachers. Teachers filled a google form on their phone for the baseline survey and Computer-Assisted Web Interviewing (CAWI) form created in SurveyCTO for the endline survey. Since these were reported data, we performed a backcheck of baseline survey by visiting 33 Anganwadis in July 2023 to ensure data quality. For more details, refer to Appendix.

In addition, we conducted two short surveys for the treatment group: an in-person visit to 35 Anganwadis in August 2023, and a brief telephonic survey of 100 Anganwadis in September 2023, out of the 407 treated Anganwadis. We also use these short surveys to correct errors in the baseline survey.

In the baseline and endline survey, teachers were asked 'how many days does a gas cylinder lasts?'. We convert the response into monthly LPG consumption in kilogram (kg). There is no difference between the treatment and control groups pre-intervention, but post-intervention, there is a decrease in monthly average LPG consumption by roughly 1 kg

(Figure 3.3). This indicates that an Anganwadi is replacing slightly less than one cylinder per year with an induction cookstove post-intervention.[5] Our preliminary calculation based on Figure 3.2 and Figure 3.3 shows that Anganwadis are saving roughly 300 INR per month on average.

Figure 3.3. LPG consumption from survey data



Notes: Author's calculation based on baseline and endline survey data from Anganwadis. There are 385 treatment and 277 control Anganwadis with 1290 observations.

We collected data on cooking time, which included preparation and cooking time for breakfast, lunch, and snacks. It is important to note that these variables are influenced by the respondent's perception and mental calculations, making them more subjective than exact measures such as 'number of days a gas cylinder lasts' or precise cooking times. Therefore, the data may be noisy, but it is the perception that most decision-makers rely on when considering a switch to another cooking method. There is noticeable bunching at intervals such as one month, two months, etc., for the 'number of days a gas cylinder lasts,' and at 15 minutes, 30 minutes, etc., for cooking minutes. So, we corrected for outliers by winsorizing at the lowest and highest bunching points in these variables.

Additionally, data on induction cookstove usage, including benefits, safety, and challenges were collected through these surveys. We also collected data on reasons for non-

[5]A standard and widely used cylinder contains 14.2 kg in India.

use of induction cookstoves post-intervention. Anganwadi-specific data such as location, student enrolment, and infrastructure were also collected to provide a better understanding of the impact of the Angan Jyothi project.

3.4 Estimation and Results

In this section, we discuss the change in LPG consumption and cooking time post-intervention using the fixed effects model as well as the difference-in-differences approach. We also explore the various barriers and enablers associated with the adoption and non-adoption of induction cookstoves within an institutional framework, where the capital cost of an induction cookstove set up is zero for teachers.

3.4.1 Impact on LPG consumption based on monthly administrative data

We estimate the change in LPG consumption using monthly administrative data from May 2022 to February 2024, along with baseline and endline survey data. Institutional setup in our case does not suffer from various household confounders. Anganwadis don't have to optimise on time and resources they have that may affect our outcome variables. Rules and menu are fixed by the government and Anganwadis follow that. Expenditure on various items is reported by Anganwadis for reimbursements and is monitored by supervisors, project officers, and other higher authorities. Given the financial implications, we believe administrative data is less prone to reporting bias compared to survey data. We intended to use all control and treatment Anganwadis, but a significant number of observations were lost during the data cleaning process. Nevertheless, we still have a sufficient number of observations for the monthly analysis.

Since administrative data is monthly, we follow a fixed effects model to analyze the changes in LPG consumption over time. This approach allows us to show the parallel trend prior to the intervention, which is essential for the difference-in-differences method

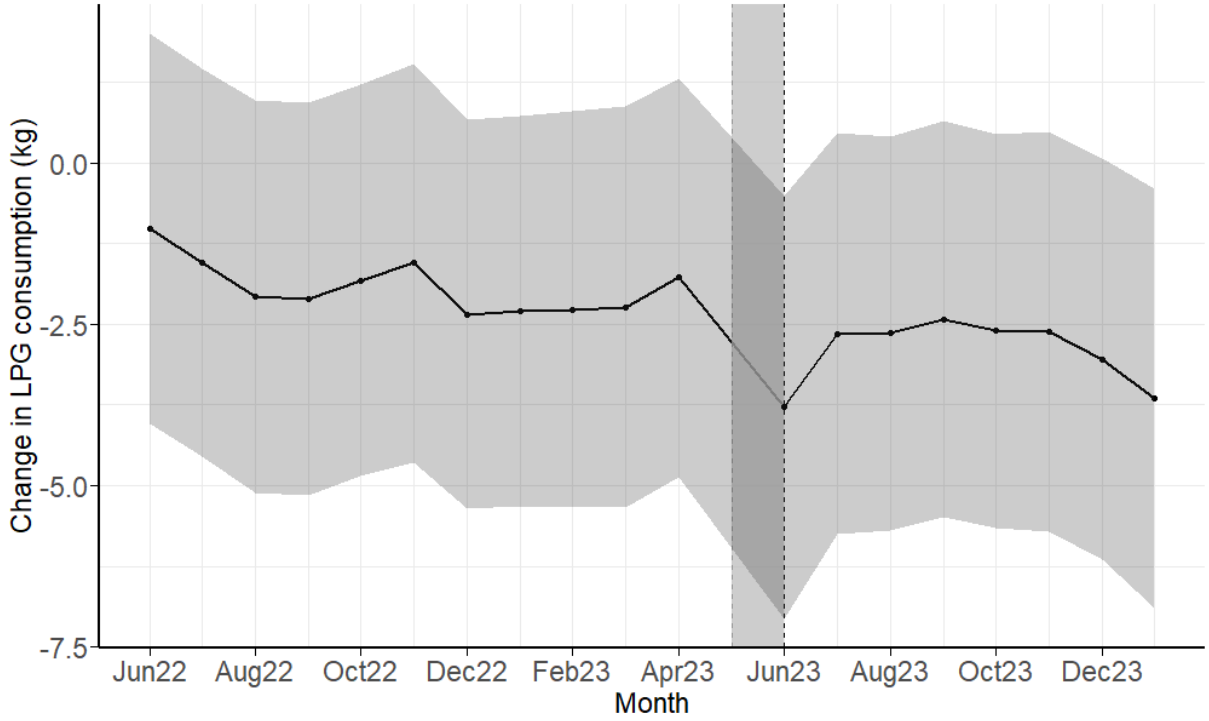
using only the baseline and the endline survey data later in this section.

$$Y_{it} = a_c + b_t + c_t T_i + dX_{it} + e_{it} \tag{3.1}$$

where Y_{it} is the outcome variable for Anganwadi i in month t. Since most of the things are standardized in an Anganwadi setup, there are negligible reasons to believe that unit or regional level unobservables, aside from the behavioral or decision-making responses of government employees at these levels, that would affect the outcome variables. Nevertheless, we control for constituency-level unobservables that may influence the outcome variables. So, a_c is the constituency fixed effect. We do not have treatment and control Anganwadi variation at lower administrative levels, such as projects and panchayats to check for robustness with project and panchayat fixed effects. b_t is the month fixed effect. T_i is the treatment dummy that takes value 1 if an Anganwadi is in the treatment group. c_t are our coefficients of interest that captures the difference in outcome between treatment and control group over the study period. X_{it} denotes the control variable, which is the total attendance (in student-days) in month t. Errors are clustered at the Anganwadi level.

Using the fixed effects model equation 3.1, we find that there is an overall decrease in the monthly average LPG consumption of Anganwadis in Figure 3.4. Standard errors are large due to the loss of observations during the data correction process, and therefore the parallel pre-trend is weakly satisfied.

Figure 3.4. Monthly trend using administrative data



Notes: The impact of the Angan Jyothi project is evaluated by comparing LPG consumption in treatment Anganwadis to control Anganwadis using the coefficients of the treatment dummy from the fixed effects model specified in equation 3.1. The corresponding 95% confidence intervals are shaded. We control for total attendance in the Anganwadi. We include constituency and month fixed effects. We cluster at the Anganwadi level. Treatment group baseline mean LPG consumption is 4.31 kg. There are 110 treatment and 168 control Anganwadis with 3511 observations.

To get an aggregate effect of the intervention, we use the following difference-in-differences model:

$$Y_{it} = a_c + b_t + cT_iP_t + dX_{it} + e_{it} \tag{3.2}$$

where P_t is the post dummy, which is 1 post-intervention (after June 2023) and 0 otherwise. Everything remains the same as in equation 3.1, except we have interacted the post dummy with the treatment dummy to obtain our coefficient of interest c.

There is incomplete adoption of induction cookstoves. As a result, we observe an intended treatment effect on the treated (ITT) of -0.75 (SE 0.20), which remains robust across all columns in Table 3.1. This translates to a roughly 17% decrease in monthly LPG consumption for an Anganwadi.

Table 3.1. Effect on LPG consumption (ITT)

	1	2	3
Treatment:Post	-0.697^{***}	-0.721^{***}	-0.747^{***}
	(0.209)	(0.201)	(0.200)
Total attendance		0.008^{***}	0.008^{***}
		(0.001)	(0.001)
Treatment	0.156	0.149	0.301^{**}
	(0.149)	(0.145)	(0.148)
Post	0.606^{***}	0.817^{***}	0.892^{***}
	(0.108)	(0.104)	(0.104)
Fixed effect			Constituency
Observations	3435	3435	3435
Adjusted R2	0.014	0.106	0.120

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the Anganwadi level.
Treatment group baseline mean is 4.31 kg.

3.4.2 Impact based on survey data

We have baseline and endline survey data on LPG consumption and cooking time. We utilize a difference-in-differences (DiD) approach to evaluate the impact of the intervention. We compare changes in outcome variables before and after the intervention between a treatment and a control group.

3.4.2.1 LPG consumption

We utilise the following regression specification to evaluate the impact on LPG consumption:

$$Y_{it} = T_i + P_t + cT_iP_t + dX_{it} + \alpha + e_{it} \tag{3.3}$$

where Y_{it} is the outcome variable for Anganwadi i in month t. T_i is the treatment dummy that takes value 1 if an Anganwadi is in the treatment group. P_t is the post dummy, which is 1 post-intervention (after June 2023). c is our coefficient of interest that captures our DiD estimate. X_{it} is the monthly average of total attendance for three months. We construct this monthly average of three months' total attendance from administrative data for both before the baseline survey and before the endline survey. Additionally, for a sensitivity check, we perform the same calculation using six months of data. We include the

same set of months to account for seasonality. Since most of the things are standardized in an Anganwadi setup, there are negligible reasons to believe that unit or regional level unobservables, aside from the behavioral or decision-making responses of government employees at these levels, that would affect our outcome variables. Nevertheless, we control for project and constituency-level unobservables that may influence the outcome variables. α denotes the constituency or project fixed effects. We do not have treatment and control Anganwadis at lower administrative level of panchayats. Errors are clustered at the Anganwadi level.

Using the DiD model equation 3.3, we find that there is an ITT of -0.62 (SE 0.28), which remains robust across all columns in Table 3.2. This translates to a roughly 10% decrease in LPG consumption for a treated Anganwadi post-intervention. This is in contrast to 17% decrease with administrative data.

Table 3.2. Effect on LPG consumption (ITT) using survey data

	1	2	3	4
Treatment:Post	-0.81^{***}	-0.72^{**}	-0.69^{**}	-0.62^{**}
	(0.24)	(0.28)	(0.28)	(0.28)
Total attendance		0.01^{***}	0.01^{***}	0.01^{***}
		(0.00)	(0.00)	(0.00)
Treatment	-0.03	0.12	0.12	0.20
	(0.23)	(0.26)	(0.25)	(0.26)
Post	-0.30^{*}	-0.19	-0.13	-0.11
	(0.18)	(0.20)	(0.21)	(0.21)
Fixed effect			Constituency	Project
Observations	1290	928	928	928
Adjusted R2	0.03	0.04	0.10	0.18

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the Anganwadi level.
Treatment group baseline mean is 6.25 kg.

Until now, we have discussed the ITT because only 61% of the 405 treated Anganwadis started using induction cookstoves for some or all purposes post-intervention. Next, we discuss the average treatment effect for adopters, using the same DiD model equation 3.3 in Table 3.3 using an adoption dummy instead of a treatment dummy. The adoption dummy is 1 for Anganwadis that have begun using the induction cookstove and 0 otherwise. We find an average treatment effect of -0.66 (SE 0.28), which remains robust across all

columns in Table 3.2. Assuming an Anganwadi reduces LPG consumption by 0.66 kg on average, translates to a roughly 10% decrease in LPG consumption for the adoption group post-intervention. This result is same as the ITT observed in Table 3.2.

Table 3.3. Effect on LPG consumption for adopters using survey data

	1	2	3	4
Adoption:Post	-0.88^{***}	-0.72^{**}	-0.71^{**}	-0.66^{**}
	(0.24)	(0.29)	(0.28)	(0.28)
Total attendance		0.01^{***}	0.01^{***}	0.01^{***}
		(0.00)	(0.00)	(0.00)
Adoption	0.61^{**}	0.44	0.25	0.17
	(0.24)	(0.28)	(0.26)	(0.24)
Post	-0.45^{***}	-0.29	-0.22	-0.19
	(0.15)	(0.19)	(0.19)	(0.19)
Fixed effect			Constituency	Project
Observations	1290	928	928	928
Adjusted R2	0.03	0.04	0.10	0.18

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the Anganwadi level.
Adoption group baseline mean is 6.65 kg.

3.4.2.2 Total cooking time

We examine the total cooking time, which is the sum of the time taken to cook and prepare breakfast, lunch, and snacks, using the DiD model equation in 3.3. We hypothesize that partial or complete cooking with induction cookstoves would save time. However, as shown in Table 3.4 for ITT and Table 3.5 for average treatment effect for adopters, we find an insignificant change in total cooking time post-intervention. However, the average treatment effect for adopters, compared to the ITT estimate shows a change in sign from positive insignificant to negative insignificant, suggesting a potential reduction in total cooking time post-intervention. This insignificance could be due to two main reasons. First, the total cooking time post-intervention included both LPG and induction cookstove use, and the change in cooking time might not be substantial enough to affect the estimate. Second, induction cookstoves were a new technology for 45 % of treated Anganwadis according to the baseline data, potentially increasing cooking time initially. Nevertheless, in the endline survey, more than 60% of Anganwadis using induction cookstoves reported

them to be convenient and time-saving.

Table 3.4. Effect on total cooking time in a day (ITT) using survey data

	1	2	3	4
Treatment:Post	8.38	3.32	3.83	5.46
	(5.43)	(6.45)	(6.45)	(6.50)
Total attendance		−0.01	0.02	0.03
		(0.02)	(0.02)	(0.02)
Treatment	−22.88***	−20.00***	−19.70***	−11.59*
	(4.82)	(5.71)	(5.57)	(6.05)
Post	−42.10***	−37.04***	−35.10***	−35.51***
	(4.33)	(4.92)	(4.89)	(4.90)
Fixed effect			Constituency	Project
Observations	1291	920	920	920
Adjusted R2	0.13	0.11	0.16	0.20

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the Anganwadi level.
Treatment group baseline mean is 128 minutes.

Table 3.5. Effect on total cooking time in a day for adopters using survey data

	1	2	3	4
Adoption:Post	−3.22	−6.39	−6.25	−4.96
	(5.38)	(6.48)	(6.46)	(6.49)
Total attendance		−0.01	0.03	0.04*
		(0.03)	(0.02)	(0.02)
Adoption	3.07	−0.14	−3.80	−1.22
	(4.99)	(5.92)	(5.84)	(6.11)
Post	−35.90***	−32.14***	−30.05***	−30.50***
	(3.38)	(4.27)	(4.24)	(4.20)
Fixed effect			Constituency	Project
Observations	1291	920	920	920
Adjusted R2	0.11	0.09	0.14	0.20

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the Anganwadi level.
Adoption group baseline mean is 139 minutes.

3.4.3 Adoption of induction cookstoves

The adoption rate has gradually increased, starting from 37 percent two months after the intervention, rising to 52 percent three months after the intervention (using a subset of data), and reaching 61 percent a year after the intervention according to the endline survey.

Out of 405 treated Anganwadis, 248 had adopted induction cookstoves in the endline survey. It is important to note that adoption remains incomplete even after the initial setup cost is removed. There are variations in the type of adoption across Anganwadis, as shown in Table 3.6. Specifically, 47 percent of them use induction cookstoves for certain dishes every day, while 25 percent use them for all dishes every day.

On the enabler side, most users of induction cookstoves reported them to be time-saving, allowing teachers and helpers to spend more time with children. Additionally, they found induction cookstoves to be convenient, cheaper than gas, safe, and tidy (Table 3.7).

On the barrier side, most users faced no problem with induction cookstoves, though some reported issues with high electricity bills, as well as socket and wiring problems (Table 3.8).

Table 3.6. Different types of induction cookstove use

Type of use	Frequency	Percentage
Occasionally	25	10
Only when LPG is over	23	9
Only to heat water	23	9
For some particular dishes every day	116	47
For all dishes every day	61	25
Total	248	100

Table 3.7. Different benefits of using induction cookstoves

	Frequency	Percentage
None	1.00	0.00
Able to spend more time with children	173.00	70.00
Safe	120.00	48.00
Can use timer function	76.00	31.00
Convenient	150.00	60.00
Cheaper than lpg gas	133.00	54.00
Keeps kitchen clean	120.00	48.00
Other	9.00	4.00

Table 3.8. Problems faced while using induction cookstoves

	Frequency	Percentage
None	198	80
There is no socket in the kitchen	16	6
The electricity bill is high	42	17
Wiring damage	19	8
Other	12	<5

3.4.4 Non-adoption of induction cookstoves

Out of 405 treated Anganwadis, approximately 39 percent were not using induction cookstoves at the time of the endline survey. Out of them, 27 percent did not use and 12 percent discontinued using induction cookstoves during the endline survey conducted a year after the treatment, which is a cause of concern. The majority faced issues with electricity infrastructure, primarily inadequate switchboards and wiring problems (Table 3.9). This is likely because the 2200-watt induction stoves require compatible higher capacity wires, switchboards, and sockets than those usually available in Anganwadis to function properly.

Table 3.9. Reasons for not using induction cookstoves

	Frequency	Percentage
The helper doesn't know how to use it	9	6
Switchboard inadequate	73	46
Satisfied with LPG	10	6
It is not working	10	6
Wiring issue	25	16
Waiting for solar	40	25
Worried about electricity bill	22	14
The electricity bill is not reimbursed	11	7
Other	7	<5

3.5 Discussion and conclusion

Current energy mix for cooking in India is not safe. Almost 50% of Indian households still use firewood for cooking, which has significant health and environmental costs. Given that Indian households are 100% electrified and only 5% use some form of electric cooking, there

is immense potential to scale electric cooking in India. As the electricity grid increasingly relies on renewable sources, transitioning from gas to induction cooking can be a promising approach to enhance both health and climate benefits, aligning with policies aimed at achieving net-zero carbon emissions (Gould et al., 2023).

The variable cost associated with any form of cooking is a major determinant of its adoption. Through an institutional framework, we provide insights on variable consumption, time, and other outcomes. Our findings indicate a 10% (0.66 kg) reduction in LPG use per month when an Anganwadi transitions to electric cooking using induction cookstoves. However, due to data limitations, we are unable to determine the corresponding increase in electricity bills. We find an insignificant but decrease in total cooking time per day post-intervention, which includes both LPG and induction cookstove use. Additionally, various enablers and barriers to electric cooking exist, even if the upfront cost of electric cooking is fully subsidized. Electric cooking is not adopted as the sole form of cooking but is stacked with LPG in this institutional case. Major barriers to adoption and discontinued adoption include electricity infrastructure like wiring, sockets, and switchboards, which may be even more challenging in most Indian households. Due to these barriers, any government program promoting electric cooking may backfire, making re-adoption even more challenging.

With an increase in renewable electricity, induction cooking is going to become cheaper and have lower lifecycle emissions. When powered by renewable energy, induction cookstoves can become the optimal solution for clean cooking due to the lack of combustion and minimal greenhouse gas emissions at the point of use (Goldemberg et al., 2018). It will undoubtedly benefit households at the point of consumption, as LPG consumption also has various forms of emission, which is not good for health. Electric cooking using renewable electricity can be a gold standard as electric cooking appliances including induction cookstoves are among the most efficient cooking technologies, aligning with the principle that energy saved is energy generated.

As Angan Jyothi is a rolling project, our research provides practical insights for the Kerala government to scale electric cooking in its 33,115 Anganwadis, a process currently

implemented in roughly 2,500 Anganwadis. The Indian government, which is in the process of expanding electric cooking, can learn from our findings for careful implementation. This is also applicable to any other government planning to expand clean cooking and reduce cooking-related emissions.

3.6 Appendix

Backcheck

We conducted a backcheck of the baseline data immediately after its collection. During this process, we identified several data quality issues across 33 Anganwadi Centres in the treatment groups, with 16 centres in Chittur and 17 in Kazhakoottam.

Regarding 'How long does one cylinder last?', the responses largely matched, with a maximum difference of one month. However, 15 out of 33 responses differed.

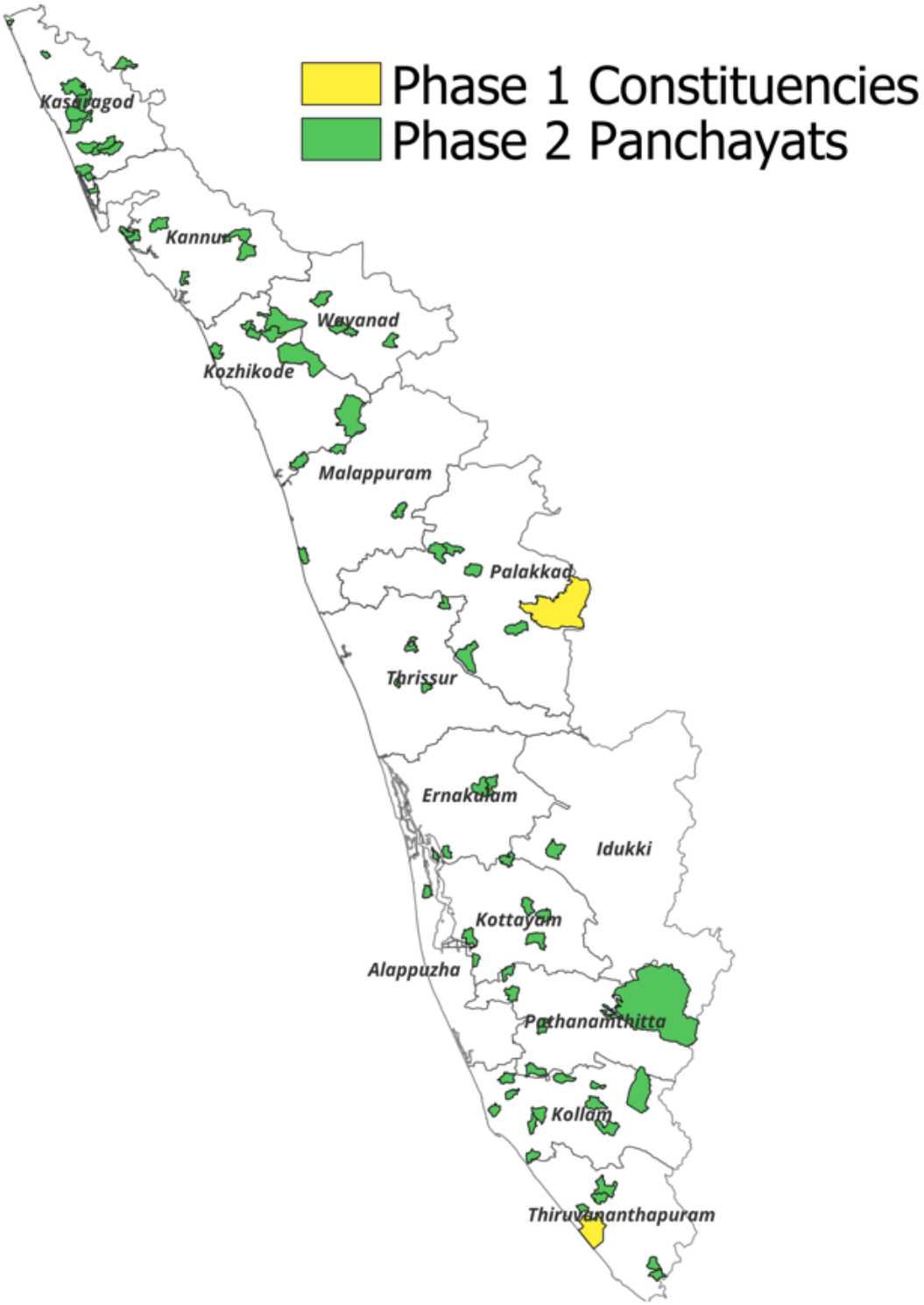
There were notable discrepancies between the baseline survey data and the backcheck data regarding the time taken to cook. For breakfast, 19 out of 33 responses differed by at least 15 minutes. For lunch, 22 out of 33 responses varied by at least 15 minutes, and for snacks, 18 out of 33 responses had a similar difference. Several factors contributed to these discrepancies. Some respondents found it difficult to estimate an average cooking time as it varies daily based on the menu. Additionally, some teachers and helpers included the entire time to cook and feed, rather than just the cooking time on LPG. In some centres, the helper answered the question while the teachers were either on leave or at a meeting (6 out of 16 in Chittur). Teachers filled out the form even though it is usually the helper who cooks in an Anganwadi.

When asked about the cheapest cooking fuel, some respondents stated that it was not possible to provide an answer without inspecting the electric bill for a month. Four responses (three from Kazhakoottam and one from Chittur) differed from the answers they had previously provided.

Regarding the time taken to refill the cylinder, a few answers differed by 2-3 days. However, in general, the teachers ensured there was an additional cylinder in store or they booked one in advance to avoid any delays.

We corrected our baseline data based on these responses.

Figure 3.5. Angan Jyothi program rollout across districts in Kerala



Notes: In Phase 1, Anganwadis across 20 panchayats in two constituencies, namely Kazhakoottam and Chittur, underwent treatment, while in Phase 2, 85 panchayats were treated. It's important to note that only 65 panchayats are displayed here due to the unavailability of recent shapefiles.

Chapter 4

Electricity as a clean cooking option: What can we learn from cross country comparison?

4.1 Introduction

The absolute number of people primarily using polluting fuels for cooking has decreased little due to rising populations, from 3 billion in 1990 to only 2.8 billion in 2020 (Stoner et al., 2021). Air pollution is one of the major health concerns globally (Cohen et al., 2017; Lelieveld et al., 2020). Exposure to household air pollution leads to increased mortality from noncommunicable diseases such as stroke, ischemic heart disease, chronic obstructive pulmonary disease (COPD), childhood pneumonia, asthma, lung cancer, among others (Balmes, 2019; Schraufnagel et al., 2019). There is a need for cleaner and more efficient cooking solutions to mitigate the adverse health and environmental impacts associated with traditional cooking practices, where electric cooking can be an another clean cooking solution.[1] Electric cooking can save time, particularly compared to traditional methods that require significant time for fuel collection and cooking, with the greatest savings seen where fuel collection is labor-intensive and advanced technologies like electricity, LPG, and biogas are used (Krishnapriya et al., 2021).

While LPG has advanced global clean cooking, its sustainable use among poor and rural households can face challenges. Large one-time costs, safety concerns, inadequate infrastructure, and high transport costs complicate usage. Remote and hilly areas face added transportation difficulties. Global price volatility and dependency on one clean fuel highlight the need for diverse energy sources (Chakravorty, Gupta, and Pelli, 2023; Parikh

[1]The major electric cooking options available include induction cookstoves, electric pressure cookers, rice cookers, hot plates, and infrared stoves.

et al., 2020). Moreover, LPG cookstoves lag significantly behind induction cookstoves in terms of efficiency. The efficiency of traditional 3-stone fires and improved cookstoves is about 10% and 23-40%, respectively; gas cooking ranges from 45-60%, electrical resistive cooking is around 75%, and inductive cooking systems can reach upto 90% (Ayub et al., 2021; Zhang et al., 2000; Sadhu et al., 2010).

When considering the two major outcomes associated with cooking, namely cost and emissions, electricity cooking can emerge as a favorable option on both fronts. In terms of costs, electricity cooking proves to be economically advantageous for households (Somanathan et al., 2022; ESMAP, 2020; Scott and Leach, 2023; Roy, 2024; Jain, Choudhury, and Ganesan, 2015). This is particularly evident in regions where electricity is competitively priced and affordable, making it attractive for individual households. Additionally, when a household transitions from gas or solid fuel cooking to electric cooking powered by renewables, it can significantly reduce overall carbon footprint. Therefore, this transition can be privately as well as socially beneficial. As electricity grids are becoming cleaner and more reliable, electric cooking holds increasing promise as a key component of the green transition in the medium to long term. This paper aims to understand the key factors influencing electric cooking adoption through a comparative study of selected countries, specifically India, Nepal, and Myanmar.

Determinants of clean cooking have been studied in various settings and contexts in literature. Using comprehensive living standard survey data from the World Bank in Ethiopia, Malawi, and Tanzania, Behera, Ali, et al. (2016) have shown that female-headed households, households with more educated heads, as well as urban and wealthy households, are more likely to use modern energy sources such as electricity and liquid petroleum gas (LPG), and are less likely to use solid fuels. In a systematic review of barriers and enablers to adoption and sustained use of LPG, biogas, solar and alcohol fuels, Puzzolo et al. (2016) have shown that the success of any clean fuel program relies on several critical factors, including the ability to meet cooking needs, the capacity to afford both the clean stove and fuel, access to a reliable and affordable fuel supply, and ensuring safe operations. In another review paper, Vigolo, Sallaku, and Testa (2018) examines

the factors that may influence the adoption of improved cookstoves (ICS). These factors include various economic conditions, socio-demographic characteristics, fuel availability, attitudes towards technology, awareness of the risks associated with traditional cookstoves and the benefits of ICS, geographic location, and social and cultural influences. Miller and Mobarak (2013) have shown through a randomized controlled trial (RCT) that women, who disproportionately bear the health costs of cooking, show a stronger preference for healthier stoves but lack the authority to make purchasing decisions within the household. Using a randomized experiment in Mali, Bonan et al. (2021) shows the significant role of information from known peers and social interactions in the adoption of improved cookstoves.

A few studies have looked at determinants of electric cooking in various settings and contexts. The availability of electricity has been shown to significantly increase the use of induction cookstoves, leading to a substantial reduction in air pollution during morning and evening cooking hours in India (Somanathan et al., 2022). Alem, Hassen, and Köhlin (2014) have shown prices of electricity and firewood and access to credit are major determinants of electric cookstove adoption using panel data spanning a decade in urban Ethiopia. A related study by Paudel, Sharifi, and Khan (2023) found that monthly expenses and the supply of electricity are significant determinants for choosing electric induction cooking. Factors such as cooking time, health advantages, environmental conditions, and information also have some influence on uptake. Another related study by Rubinstein et al. (2022) identify several factors influencing the adoption of electric pressure cookers in urban Cameroon through a mixed-method approach, including quantitative and qualitative analyses. Key barriers and enablers include the cost of appliances and energy, the reliability of the electricity supply, perceived safety concerns, reluctance to replace traditional fuels or LPG with electric cooking, and a lack of policy commitment.

However, there is a lack of systematic studies across low and lower-middle-income countries on the crucial determinants of electric cooking adoption, especially those amenable to policy intervention, such as reliability and prices. Our dual approach, combining econometric analysis with qualitative analysis aims to significantly enhance

understanding of these critical issues. We utilize one the first such comprehensive household energy surveys like IRES and MTF conducted in our study countries to explore the impact of factors such as electricity reliability and quality, pricing, gender dynamics, and other variables on the adoption of electric cooking. These relationships may be influenced by diverse country-specific factors such as income levels, recent electrification, cooking preferences, and more. We conduct qualitative analysis to complement our econometric analyses to provide additional insights into the determinants of electric cooking adoption. While the absence of standard quasi-random variation for identification is anticipated, the qualitative surveys offer comprehensive information that facilitates the understanding of crucial factors. A more comprehensive understanding of this issue could inform policies aimed at substantially expanding the use of electric cooking. This, in turn, would contribute to lowering exposure to air pollution and enhancing overall welfare, particularly among women who predominantly bear the responsibility for household cooking and fuel collection.

Using a quantitative cross-sectional model, we find that hours of electricity supply per day, wealth, monthly consumption expenditure, urban population, age, education, gender and monthly fuel expenditure are correlated with the use of electric cooking. However, these correlations are country-dependent. For example, electricity reliability is not correlated with the increased use of electric cooking in India but it is correlated in Myanmar and Nepal. Additionally, through qualitative key informant interview (KIIs), we found that these factors are highly context-dependent. A strong correlation in one context may not hold true in another. We identified a list of factors affecting the adoption of electric cooking that would not have been possible to uncover through quantitative analysis alone. However, these factors need to be tested with larger samples. From the demand side, we find that electric cooking is mostly used as a stack. Induction cookstove failures due to coil burning or circuit problems, combined with a lack of local repair shops, can be barriers to adoption. Additional barriers include the quality of electricity supply, inadequate household electricity infrastructure (such as wiring and switchboards), past familiarity with LPG, age, high fuel costs, peak and monsoon seasons affecting electricity

quality, the need for induction-compatible vessels for large families, issues with cockroaches and moisture inside induction cookstoves, and the need for an extra burner. On the other hand, the speed of cooking and the ready availability compared to LPG fuel are enablers of adoption. The electric cooking market is not a concern, as electric cooking appliances are available in nearby town markets, and online shopping sites deliver to most rural areas in India and Nepal.

The structure of the paper is as follows: Section 2 describes the data. Section 3 describes the estimation and results using quantitative identifying a list of country-specific factors correlated with the adoption of electric cooking, as well as household-specific enablers and barriers to adoption. Section 4 presents qualitative insights on the enablers and barriers to electric cooking, offering a well-rounded understanding of the topic. Section 5 briefly discusses the results and concludes with policy implications.

4.2 Data

We utilize India Residential Energy Survey (IRES), conducted by the Centre for Energy, Environment, and Water in 2019-20, and the World Bank's Multi-Tier Framework survey data for Nepal and Myanmar, conducted between 2016 and 2018. IRES and MTF surveys are among the first comprehensive energy surveys that go beyond just the 'primary cooking fuel.' They provide information as detailed as the proportion of time specific stove types as used for morning, afternoon, and evening meals, their frequency of use, duration etc. Additionally, the surveys include details on the reliability and predictability of electricity supply and electricity billing, among other factors. We show a long list of variables including control variables in summary statistics for India, Nepal and Myanmar in Appendix Tables 4.5, 4.6, 4.7, 4.8, 4.9, 4.10, 4.11, 4.12, and 4.13. Leveraging this primary data, we aim to identify determinants of electric cooking adoption, such as electricity reliability, prices, incomes, gender, and other variables. The primary outcome variables of interest are the use of electric cooking for any of the cooking purposes and the use of electric cooking for the main cooking purpose.

For the qualitative case studies, KIIs were conducted with household members, including primary cooks or heads of households based on availability. Questionnaires of this key informant interview are motivated mostly from World Bank's Multi-tier Framework survey data. Along with demand-side KIIs, we also conducted supply-side interviews with retailers and wholesalers in the same areas where household KIIs were performed. These case studies were carried out in part of the countries, where there is possibility of finding some electric cookstove users along with non-users to distinguish if there are some factors critical to electric cookstove adoption.

4.3 Estimation and results

We utilize a combination of quantitative and qualitative methodologies for data analysis. Specifically, we use cross-sectional regression analysis to examine the correlates of electricity-based cooking across our study countries. The regression analysis involves modeling the use of electric cooking for any purposes and the use of electric cooking for main purpose against variables such as electricity reliability and quality, income, gender indicators, education, and other relevant factors. Given the cross-sectional nature of the MTF data, efforts are made to control for important determinants of dependent variables, acknowledging the potential for omitted variable bias, particularly in the electricity variables, which are the primary focus. Further, qualitative analysis allows us to capture other factors that may not be available in data.

4.3.1 Descriptive Statistics

According to the India Residential Energy Survey 2020, there is a noticeable disparity between the level of electrification and the utilization of electricity as the primary cooking fuel in rural, urban, and all-India contexts (Figure 4.3). Across the nation, functional electricity reached an impressive 97% of households, with urban areas leading at 99%. However, when it came to the choice of cooking fuel, urban households predominantly relied on clean LPG (96%), while rural areas lagged behind, with 80% using LPG and a

substantial 73% still relying on traditional solid fuel for any of the cooking (Appendix Tables 4.6 & 4.7). Surprisingly, the adoption of electricity remained low, accounting for less than 5% of households nationwide for any of the cooking. This gap between electric cooking and household electrification is evident in other countries as well, as shown in Figure 4.3. This indicates that the gap in clean cooking can be bridged by adopting electric cooking.

In Nepal, 90% of the population has access to electricity (Our World in Data, 2020). A remarkable 98.6% of this electricity is generated from hydro sources, with an additional 1.4% coming from solar, and only 11.7% of the total electricity supply is imported (IEA, 2021). In Nepal, where the share of residential electricity consumption out of total electricity consumption is the highest at 43% (IEA, 2021), there lies a significant opportunity for emission reductions with electric cooking. Furthermore, with only 1% of the population utilizing electric fuel for any cooking purpose (Appendix Table 4.8), there's a substantial potential for the expansion of electric cooking.

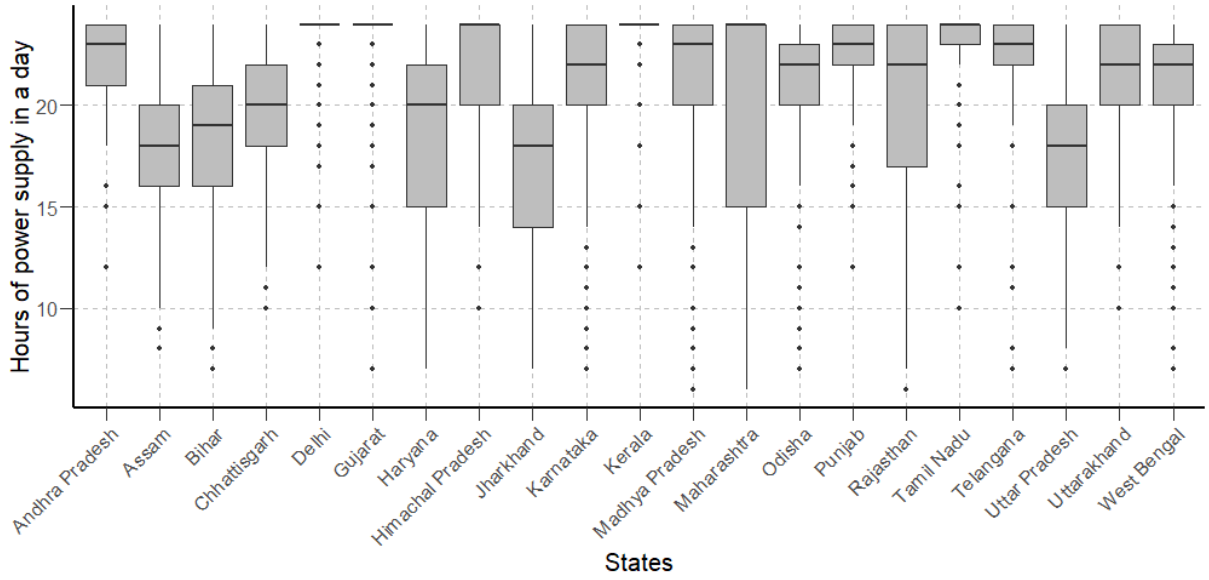
Table 4.1 presents the adoption rates of electric cooking across three countries: India, Nepal, and Myanmar, with significant regional disparities. In India, only 5% of households use any form of electric cooking, and only 1% rely on it as their primary cooking method, with urban areas showing slightly higher adoption rates than rural ones. Nepal shows a higher overall adoption, with 21% of households using them. This rate is higher in urban areas (31%) compared to rural areas (9%). Myanmar shows the highest adoption rates among the three countries, with 24% of households using some form of electric cooking and 22% using it as their main method. The urban adoption rate in Myanmar is high, with 42% of households using electric cooking and 38% using it as their primary method, compared to 32% and 28% in rural areas, respectively. These findings indicate that while urban areas are leading in the adoption of electric cooking, there is significant potential to increase usage in rural areas, thereby bridging the gap in clean cooking practices. One of our main control variable, 'Hours of electricity supply in a day' shows high variation in reliability across the states and within the state in Table 4.1.

Table 4.1. Outcome variables

		All		Urban		Rural	
		Mean	Obs	Mean	Obs	Mean	Obs
India	Any electric cooking	0.05	12459	0.10	4253	0.02	8206
	Main electric cooking	0.01	12459	0.02	4253	0.00	8206
Nepal	Any electric cooking	0.21	5776	0.31	3200	0.09	2576
	Main electric cooking	0.00	5776	0.01	3200	0.00	2576
Myanmar	Any electric cooking	0.24	3383	0.42	1684	0.32	1699
	Main electric cooking	0.22	3383	0.38	1684	0.28	1699

Source: IRES for India and MTF for Nepal and Myanmar

Figure 4.1. Reliability variation across states in India



Source: IRES conducted in 2019-20

Notes: The box shows the interquartile range (IQR), with its edges indicating the third (Q3) and first quartiles (Q1). The horizontal line inside the box is the median. Whiskers extend to the smallest and largest values within 1.5 times the IQR. Dots outside the whiskers are outliers.

4.3.2 Regression

Due to the lack of panel data on these energy surveys, we follow a cross-sectional model with control for important determinants of outcome variables. We add a comprehensive list of control variables that can explain our outcome variables for a robust correlation

analysis.

$$Y_i = \beta_k X_k + \alpha_s + e_i \tag{4.1}$$

where, Y_i is the outcome variable such as the use of electric cooking for any purpose (any electric cooking), and the use of electric cooking for the main purpose (main electric cooking) for household i. X_k are a list of explanatory variables. Explanatory variables are not homogeneous across our study countries. So, we are unable to include the same set of variables in each country. Nevertheless, we include a comprehensive list of variables that may affect our outcome variables. While there are multiple measures of electricity reliability available in the data, they are all highly correlated among each other. So, we use only hours of power supply in a day (Electricity hours). We control for the price of cooking fuels like electricity and LPG as well as other time invariant factors using state fixed effect, assuming it to be mostly the same within a state.[2] α_s is a fixed effect for states. We are not controlling for lower administrative units, which is an enumeration area (or village), because reliability measures are likely to be the same within an enumeration area. We cluster at the enumeration area level.

We show the determinants of electric cooking using equation 4.1 in Tables 4.2, 4.3, and 4.4 for the whole sample as well as for urban and rural samples separately. Each table represents one separate study country.[3] People are more likely to use electric cooking in urban areas. We find that 'electricity hours' is not correlated with adoption of any electric cooking in India, while it is strongly correlated to adoption of electric cookin in Nepal for any electric cooking as well as main electric cooking in Myanmar. One hour increase in electricity supply per day in Nepal leads to adoption of electric cookin by 2%. Similarly, one hour increase in electricity supply per day in Myanmar leads to adoption of electric cooking for any purpose by 2% and adoption of electric cooking for primary purpose by 3%. Additionally, Monthly consumption expenditure per capita is associated with use of electric cooking in urban India, urban Nepal and rural Nepal. Wealth-index[4]

[2]The price of these fuels varies for different households based on subsidies and slab systems.

[3]We are unable to run a regression for India with electricity as a primary fuel due to insufficient observations.

[4]Wealth-index is constructed using principal component analysis on a list of assets like own home, flushtoilet, pucca house, vehicles, electronics etc.

is positively correlated with the use of electric cooking in India and urban Nepal but not in Myanmar. Urban areas are more likely to use any electric cooking appliances in India, Nepal but not in Myanmar. Education is positively associated with the use of electric cooking across all three countries.

There are other factors like, familiarity with LPG, age of the household head, gender, smoke in the kitchen due to traditional cooking, monthly expenditure on electric cooking and LPG and availability of solid fuels like charcoal are associated with use of electric cooking but they are not consistent across our study countries and across urban and rural area. The signs of many factors that can determine the adoption of electric cooking are anticipated, our qualitative interviews confirm many of these factors. However, some variables do not show the expected signs like a household female member being part of women's group in Nepal, availability of wood in Myanmar etc. Therefore, there is a need for rigorous econometric analysis to identify these factors more accurately, incorporating more related variables and a robust counterfactual design. In the following section, we complement our quantitative analysis with qualitative insights to better understand the factors that may affect the adoption of electric cooking. Using qualitative analysis, we can identify additional factors not captured in the survey data that may influence the adoption of electric cooking.

Table 4.2. Determinants of electric cooking in India

	Any electric cooking		
	All	Urban	Rural
Electricity hours	-0.001	0.002	-0.001
	(0.001)	(0.002)	(0.000)
Wealth index	0.028***	0.039***	0.015***
	(0.003)	(0.004)	(0.003)
Log(Consumption)	0.005	0.011	0.001
	(0.005)	(0.011)	(0.004)
Urban	0.025***		
	(0.008)		
HH size	0.002	0.005*	0.001
	(0.001)	(0.003)	(0.001)
Gender (Female =1)	0.004	0.012	0.002
	(0.007)	(0.015)	(0.006)
Education (Categories)	0.004***	0.010***	0.001
	(0.001)	(0.003)	(0.001)
LPG	-0.026***	-0.056**	-0.007*
	(0.005)	(0.025)	(0.004)
Observations	12,079	4,224	7,855
State FE	Yes	Yes	Yes
R^2	0.07	0.08	0.02

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the EA/Village level.

Any electric cooking - Use of electricity for any cooking purpose

Electricity hours - Hours of electricity in a day

Log(Consumption) - Log of monthly consumption expenditure per capita

Education (Categories) are from 1 to 8.

Gender and education of prime income earner.

Table 4.3. Determinants of electric cooking in Nepal

	Any electric cooking		
	All	Urban	Rural
Electricity hours	0.020***	0.022***	0.012**
	(0.003)	(0.003)	(0.006)
Log(Consumption)	0.065***	0.092***	0.010
	(0.016)	(0.022)	(0.016)
Wealth index	0.057***	0.070***	0.009
	(0.007)	(0.008)	(0.012)
Urban	0.070***		
	(0.025)		
HH size	-0.004	-0.000	-0.006
	(0.004)	(0.006)	(0.006)
Bank account	0.086***	0.070***	0.098***
	(0.016)	(0.021)	(0.023)
Informal account	0.046**	0.037*	0.066**
	(0.018)	(0.022)	(0.030)
Credit availability	0.067	0.068	0.092*
	(0.046)	(0.052)	(0.053)
Women's mobility	-0.002	-0.005	0.001
	(0.007)	(0.009)	(0.011)
Women's groups	-0.084	-0.150*	0.044
	(0.074)	(0.090)	(0.049)
Age	0.001***	0.001*	0.002**
	(0.001)	(0.001)	(0.001)
Gender: Female = 1	0.041**	0.052**	0.006
	(0.019)	(0.025)	(0.026)
Highest education	0.020***	0.018***	0.021***
	(0.003)	(0.003)	(0.004)
Observations	3,820	2,565	1,255
State FE	Yes	Yes	Yes
R^2	0.19	0.20	0.09

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the EA/Village level.

Any electric cooking - Use of electricity for any cooking purpose

Electricity hours - Hours of electricity in a day

Log(Consumption) - Log of monthly consumption expenditure per capita

Education - Categories range from 0 to 5.

Gender, age and education of household head

Table 4.4. Determinants of electric cooking in Myanmar

	Any electric cooking			Main electric cooking		
	All	Urban	Rural	All	Urban	Rural
Electricity hours	0.024***	0.024***	0.023***	0.027***	0.027***	0.019**
	(0.002)	(0.002)	(0.007)	(0.002)	(0.002)	(0.008)
Log(Consumption)	0.029	0.007	0.061*	0.025	-0.012	0.077**
	(0.023)	(0.031)	(0.034)	(0.022)	(0.028)	(0.031)
Wealth index	-0.025	-0.026	-0.028	-0.014	-0.026	-0.010
	(0.021)	(0.028)	(0.030)	(0.022)	(0.028)	(0.032)
Urban	0.007			-0.012		
	(0.045)			(0.044)		
HH size	-0.015**	-0.020**	-0.008	-0.010	-0.017**	0.002
	(0.007)	(0.008)	(0.012)	(0.007)	(0.008)	(0.013)
Smoke problem	0.065*	0.074*	0.065	0.066**	0.089**	0.041
	(0.033)	(0.044)	(0.052)	(0.033)	(0.044)	(0.048)
Electric cooking exp.	-0.136***	-0.135***	-0.126**	-0.141***	-0.156***	-0.098*
	(0.037)	(0.049)	(0.053)	(0.037)	(0.050)	(0.050)
LPG cooking exp.	0.134***	0.104***	0.157***	0.115***	0.079**	0.130***
	(0.029)	(0.038)	(0.043)	(0.028)	(0.037)	(0.044)
Wood availability	0.037	0.068**	0.003	0.052**	0.079**	0.027
	(0.027)	(0.034)	(0.043)	(0.026)	(0.033)	(0.041)
Charcoal Availability	-0.049	-0.095**	0.005	-0.048	-0.077*	-0.016
	(0.033)	(0.047)	(0.046)	(0.030)	(0.043)	(0.042)
Bank account	0.036	0.012	0.099*	0.056	0.040	0.111**
	(0.040)	(0.053)	(0.055)	(0.036)	(0.047)	(0.050)
Informal account	0.010	0.001	0.012	0.062	0.012	0.101*
	(0.051)	(0.062)	(0.078)	(0.041)	(0.057)	(0.059)
Credit availability	0.000	-0.012	0.018	0.018	-0.000	0.040
	(0.036)	(0.044)	(0.063)	(0.034)	(0.044)	(0.055)
Age	-0.001	-0.000	-0.002*	-0.001	-0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender: Female = 1	-0.058**	-0.042	-0.079*	-0.066**	-0.043	-0.094**
	(0.027)	(0.035)	(0.042)	(0.027)	(0.034)	(0.045)
Highest education	0.057***	0.059***	0.051***	0.063***	0.061***	0.060***
	(0.010)	(0.014)	(0.014)	(0.010)	(0.012)	(0.015)
Observations	2,171	1,239	932	2,171	1,239	932
State FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.132	0.164	0.103	0.147	0.191	0.109

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are in parentheses. Cluster at the EA/Village level.

Any electric cooking - Use of electricity for any cooking purpose

Main electric cooking - Use of electricity for primary cooking purpose

Electricity hours - Hours of electricity in a day

Log(Consumption) - Log of monthly consumption expenditure per capita

Education - Categories range from 0 to 5.

Gender, age and education of household head

4.4 Qualitative analysis

We describe data, enablers and barriers for electric cooking and other findings in this section. We could not do qualitative analysis for Myanmar due to lack of local support. We conducted KIIs related to electricity supply and cooking practices with households and nearby retailers in Tamil Nadu (South India) in June 2023, Uttar Pradesh (North India) in August 2023, Bihar (East India) in August 2023, and Nepal in November 2023. Induction cookstoves are the most popular electric cooking appliance in India. We chose Tamil Nadu because it has good electricity reliability and the highest share of induction cookstove usage (approx. 13.5%) among all the states in India (IRES 2020). We chose Uttar Pradesh and Bihar because they have low reliability. This enabled us to capture variations in electricity reliability and electric cooking scenarios across the country (See Appendix Figure 4.1 for reliability variation across states in India). Sample selection method was purposive to find some households using electric cooking and non-electric cooking households in the same area. Our sample includes more rural households than urban ones.

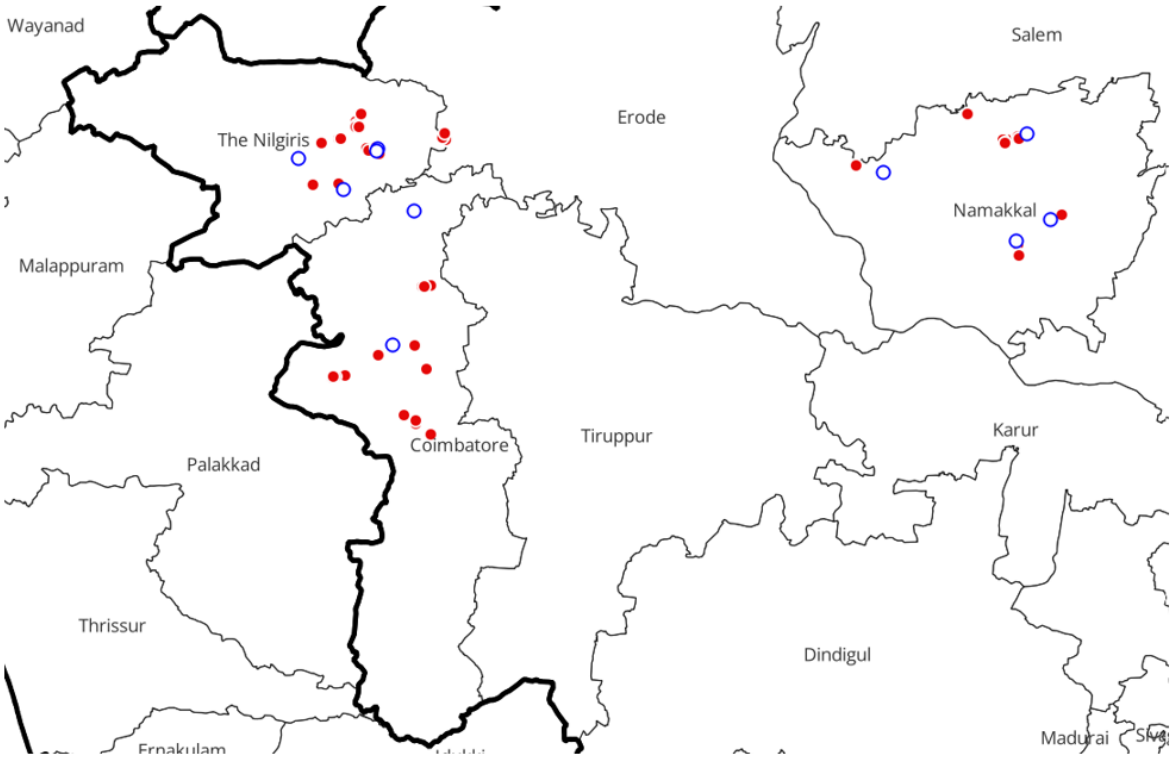
4.4.1 Qualitative Data

In Tamil Nadu, we did KIIs with 79 households and 10 retailers (See Figure 4.2). Among these households, 49 had adopted induction cookstoves. Of these, 44 were current users, with 4 utilizing them as their primary cooking method, 37 as a secondary means, 3 as neither primary nor secondary, and 5 were past users of induction cookstoves. More non-primary users of Induction cookstoves indicates the prevalence of electric fuel as a stack. The study was conducted in three districts: Coimbatore, with high reliability; Namakkal, with low-reliability; and the Nilgiris, a hilly region where a state government program to distribute free induction cookstoves to all households was launched in 2011.

We found that most of the users of induction cookstoves reported that their induction cookstove had broken down (36 out of 49) indicating the need for better quality and long lasting electric cooking devices. Electricity infrastructure is another major barrier with 12

out of 49 Induction cookstove users encountering wiring or switchboard problems.

Figure 4.2. Observations from Tamil Nadu field visit



Notes: Red dots are households and blue dots are nearby retailers. Other Indian states and Nepal KIIs have similar spatial patterns for households and retailers.

We conducted a field visit to three villages in Uttar Pradesh: two in Sultanpur district, and one in Varanasi district. During these visits, we did KIIs with a total of 9 households, including both users and non-users of induction cookstoves. We also visited a village in Begusarai (Bihar) and conducted the same KIIs with 5 households, all of them were using induction cookstoves for secondary use except one. In Nepal, non-systematic interviews were conducted with eight households in the remote Baireni village, located in the Dhading District within the Bagmati province of central Nepal (approximately 3 hours and 60 km from Kathmandu). Additionally, we conducted a non-systematic interview with a retailer at a prominent electrical market in Kathmandu. In the following section, we discuss demand and supply side factors that may affect adoption of electric cooking for Tamil Nadu, Uttar Pradesh, and Bihar state in India as well as Bagmati province in

Nepal respectively.

4.4.2 Enablers and barriers

In Tamil Nadu, a strong past familiarity with LPG remained evident, making it the primary cooking fuel for most households. Some households, particularly primary users of traditional fuels and past users of induction cookstove, expressed concerns about the quality of induction cookstoves, citing issues such as coil burning and inadequacy of electrical wiring needed to power heavy appliances like induction cookstoves.[5] This suggests that the quality of induction cookstoves and the electricity infrastructure to support their use is one of the barriers to the adoption of electric cooking. Additionally, technology barriers were noted, particularly among older individuals who found induction cookstoves challenging to use. The lack of affordable local repair shops also emerged as a potential barrier. Some wealthier households preferred to replace rather than repair malfunctioning induction cookstoves due to high transaction cost. This highlights the need for more accessible and affordable local repair services, which may eventually develop when there is high penetration of electric cooking appliances. High variable costs were another deterrent, with at least one past user of induction cookstoves discontinuing their use due to the high electricity costs associated with boiling water for drinking and bathing, along with frequent induction cookstove failures. Despite these challenges, some benefits of induction cooking were recognized, particularly the speed of cooking, which was identified as a primary advantage.

Electricity reliability did not emerge as a major issue, with most households reporting nearly uninterrupted 24-hour electricity service, except for occasional disruptions during the monsoon season. However, seasonal reliability issues were noted, as some households experienced unreliable electricity during the monsoon and summer seasons. This suggests that while the general reliability of electricity is high, seasonal variations can still pose challenges for consistent use of electric cooking appliances. In the Nilgiris, of the 22 households that received free induction cookstoves in 2011, 11 acquired an additional

[5]Induction cookstove capacity ranged between 1200 to 3000 watt.

induction cookstove when the previous one stopped working, resulting in sustained use for 55% of the households after 12 years. This suggests that experience leads to a high demand as Tamil Nadu has the highest induction cookstove usage among Indian states, with 13% of its population using them.

Electric cooking appliances such as one-hob induction cookstoves, rice cookers, ovens, and kettles are readily available in district and sub-district/block markets in Tamil Nadu, so availability of electric cooking appliances is not an issue. Among these appliances, induction cookstoves were the most popular, whereas rice cookers were significantly more expensive, costing more than twice as much as induction cookstoves and roughly half the upfront cost of setting up an LPG cookstove. Common complaints from customers regarding induction cookstoves included teflon glass breakage, moisture seeping inside the body, and circuit and wire burns. Retailers typically offer a one-year warranty on induction cookstoves, which is generally the same as LPG stoves. In contrast, rice cookers usually came with a five-year warranty, indicating a longer expected lifespan.

Electricity supply shortages were a significant issue in Uttar Pradesh, with daily outages lasting between 2 to 12 hours and multiple disruptions affecting daily life. Seasonal demand peaks in the summer further impacted the reliability of electricity supply in some areas. Additionally, utensil compatibility was a notable concern for induction cooking, as some households needed larger induction-compatible vessels that were not available in the market. Inconsistent billing by customers and infrequent meter reading by distribution companies were also common issues, indicating a poor demand and supply equilibrium for electricity quality. Cravings for traditionally cooked food were also noted, with one user who had switched to induction cooking for most of their meals still occasionally used traditional methods, once in a month. Another household highlighted a preference for the quick availability of electricity for induction cooking over LPG, as there is some transaction cost involved for booking and refilling LPG cylinders. Lastly, a poor household used to buy cow dung cakes as cooking fuel, especially during the monsoon season, as they found it more economical than LPG. In Varanasi district, an extended interaction with a household member revealed the presence of unmetered or stolen electricity serving as an

incentive for some households to adopt electric cooking. An outcome, which is obvious due to zero cost of a fuel but generally unreported.

In Bihar, electricity reliability was a significant concern in the village, with frequent outages lasting between 4-7 hours per day. Data from a nearby power distribution substation confirms this finding for the village and all neighboring villages it serves. The substation operated on a quota-based system, where a specified number of power units is allocated by the higher authorities each day. The substation operator was then responsible for distributing electricity equally among seven feeders, resulting in outages that often occurred without prior notice. Despite these challenges, one household had been using an induction cookstove for five years, while other users had adopted induction cookstoves more recently, within the last six months. The fixed monthly electricity cost for that long-term user acted as an incentive for their choice in the past, effectively providing a zero marginal cost for electricity.

In Uttar Pradesh and Bihar, the market for electric cooking appliances is not a problem. Household interactions indicated that induction cookstoves are available in the nearest sub-district/block markets, typically located 0 to 10 kilometers from the villages. Additionally, online shopping sites like Flipkart and Amazon are accessible to these households, providing further options for purchasing electric cooking appliances.

In Nepal, all induction cooking households were a part of a project that received constant support from project management, [6] leading to a higher possibility of repurchasing induction cookstoves. The cost of an induction cookstove was 4000 NPR (approximately 2500 INR or 30 USD), slightly higher than the price in India, which is 2000 INR. Interestingly, reliability is not a problem for these households, although issues like cockroaches causing the induction cookstove to trip were noted. A sophisticated smart meter in these households cost 14000 NPR (105 USD). Despite this advancement to monitor their energy use instantly, switching entirely to induction cooking was challenging. Some households used gas when there was no electricity or when they required extra burners. Additionally, the fear of electric shocks among the elderly was a concern, with only children using

[6]Note that these households were selected purposely because of local support.

appliances like kettles in some homes. Adult children in these households are highly mobile and often purchase induction cookstoves and rice cookers from Kathmandu. In some cases, small electric flour mills are also present, which could potentially increase electricity costs due to higher usage falling into a higher billing slab.

On the supply side, the market for electric cooking appliances in Kathmandu, included induction cooktoves, infrared stoves, and kettles. Infrared stoves were the most popular due to the requirement for special utensils with induction cookstoves. The retailer stopped stocking rice cookers to focus on other products indicating a decline in their market. Induction cookstoves from the Chaudhary Group, along with brands like Prestige, Pigeon and Maharaja were prominent, with Maharaja being the best-selling brand. The Maharaja induction cookstove, featuring a 2000-watt capacity, was priced at 3500 NPR (approximately 26 dollars). The supply chain involved unassembled products being shipped from China to Vizag, a southern Indian port city, and then transported to Delhi and Mumbai for assembly. The final products were then distributed throughout India and Nepal. During the lockdown in 2020, a shortage of LPG due to tightened export restrictions from India led to an increase in sales of infrared and induction cookstoves. However, sales of infrared stoves dipped after reports that the glass of the stove could break if wiped while still hot. Only two people demanded two-hob induction cookstoves in the last two years, which is in contrast to the need for extra burners. Customers also came from nearby districts, indicating a lack of such shops in those districts including district towns. Daraz, an Alibaba alliance, is the online shopping site that delivers across Nepal. The retailer reported that load shedding and voltage issues were prevalent in Kathmandu city due to huge load from the growing population. Cockroaches entering induction cookstoves and causing damage was the major issue reported by customers which we also found in household KIIs in Nepal.

From the policy side, several developments aimed to improve electricity infrastructure and enhance the quality of power supply, which may further encourage the adoption of electric cooking. The Nepal Electricity Authority upgraded wooden poles to steel poles and, subsequently, to covered conductor poles. It was claimed by one of the officials of

Nepal Electricity Authority that 90 percent of households in Kathmandu had induction cookstoves indicating a high adoption rate in the city. They had plans to reduce tariffs in the future and achieve 100 percent electrification within the next one and a half years. Additionally, the construction of mini hydro power plants near Kathmandu was underway to help alleviate the power load.

These findings are based on small samples, which do not provide any quantitative conclusion but open the way for further data collection, policy and research on potential factors affecting the adoption of electric cooking.

4.5 Discussion and conclusion

Air pollution is a global concern that leads to the deterioration of health and the environment, causing non-communicable diseases, disability, and death. Household cooking, a daily activity for many, still relies on polluting fuels for 2.8 billion people. Shifting to clean cooking methods would offer significant personal and social benefits. Although LPG has made substantial progress, it is not sufficient on its own. Electric cooking can be another clean solution, but the challenge lies in encouraging, implementing, and scaling its use. While the determinants of clean cooking have been extensively studied, only a few studies have focused on the determinants of electric cooking.

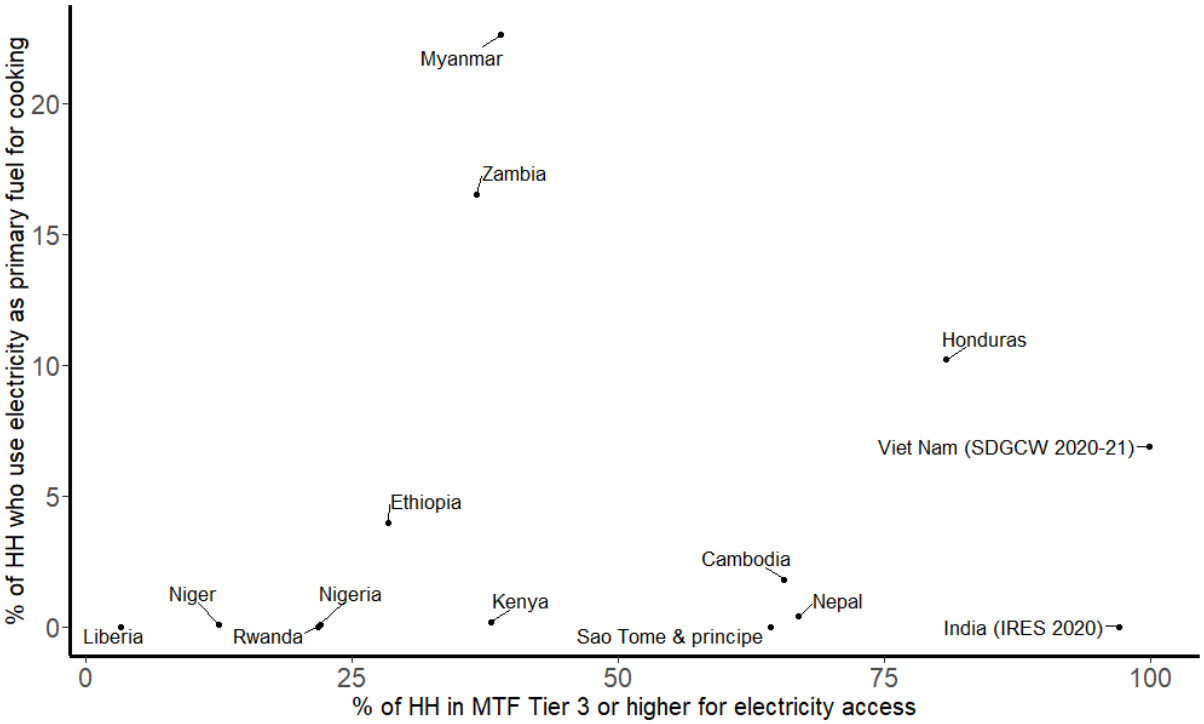
We look at this both quantitatively and qualitatively. Quantitatively, we find that electricity reliability, wealth index, monthly consumption expenditure per capita, monthly fuel expenditure of electricity and LPG, education and other socioeconomic factors are correlated with electric cooking adoption, which are country-specific. Additionally, we add to these findings using qualitative KII. We find that electric cooking is primarily used as a stack. While the speed of cooking, ready availability of electricity in the household, and the supply of electric cooking appliances can favor the adoption of electric cooking, there are numerous household-specific barriers. Major barriers can be poor electricity quality during peak and monsoon seasons, the quality of electric cookstoves, the lack of local repair shops for electric cooking appliances, and incompatibility of household

electricity infrastructure like wiring and switchboards to high capacity electric cooking appliances. Most of the factors we identify align with existing quantitative literature on the determinants of clean cooking, including electric cooking. However, we also highlight context-specific factors that are less discussed, such as electricity quality during peak and monsoon seasons, the quality of electric cookstoves, the lack of local repair shops, and inadequate household electricity infrastructure.

To scale electric cooking, it must be accompanied by increased generation capacity and high-quality transmission and distribution infrastructure. Similarly, other barriers can be addressed accordingly. While this study does not employ a counterfactual design, it provides a comprehensive view of multiple factors that may not be captured in a causal study. We identified a list of demand and supply side factors that could be further explored for research, included in data collection surveys, and considered by governments to effectively scale electric cooking.

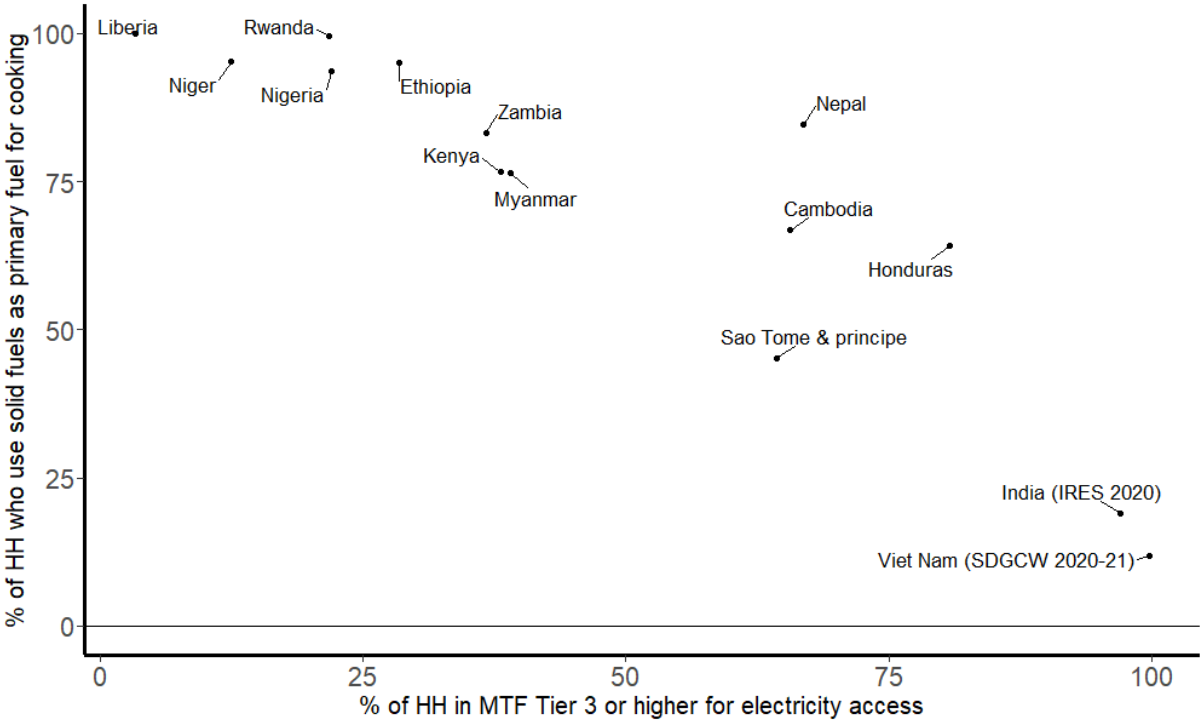
4.6 Appendix

Figure 4.3. Electricity as the primary fuel vs good quality electricity access



Notes: Based on various MTF diagnostic reports unless otherwise indicated. The figures for India and Vietnam represent electricity access only, not MTF Tier 3 access. MTF Tier 3 includes power capacity from 800W to 1999W, electricity availability for 8 to 16 hours during the day and 3 to 4 hours in the evening, with the cost of a standard consumption package (365 kWh/year) being less than 5% of household expenditure or income.

Figure 4.4. Solid as primary fuel vs good quality electricity access



Notes: Based on various MTF diagnostic reports unless otherwise indicated. The figures for India and Vietnam represent electricity access only, not MTF Tier 3 access. MTF Tier 3 includes power capacity from 800W to 1999W, electricity availability for 8 to 16 hours during the day and 3 to 4 hours in the evening, with the cost of a standard consumption package (365 kWh/year) being less than 5% of household expenditure or income.

Table 4.5. Summary Statistics for India - Whole Sample

	Obs	Mean	SD	Minimum	Maximum
Urban dummy	14851	0.34	0.47	0.00	1.00
Any Electric Cooking	14851	0.05	0.22	0.00	1.00
Main Electric Cooking	14851	0.01	0.09	0.00	1.00
Electric coil (Dummy)	14404	0.01	0.08	0.00	1.00
Induction cookstove (Dummy)	14404	0.02	0.15	0.00	1.00
Micro-wave (Dummy)	14404	0.02	0.12	0.00	1.00
Oven/griller/toaster (Dummy)	14404	0.01	0.07	0.00	1.00
Rice cooker (Dummy)	14404	0.02	0.14	0.00	1.00
Gender (Female = 1)	14851	0.11	0.31	0.00	1.00
Education level (Categories)	14851	4.35	2.06	1.00	8.00
Highest Education - Any member	14851	5.62	1.86	1.00	8.00
HH size	14851	5.05	2.24	1.00	25.00
Monthly expenditure (INR)	12459	8176.41	5383.03	1000.00	100000.00
Hours of power supply in a day	14342	20.55	4.06	6.00	24.00
Power cut informed (Dummy)	12299	0.12	0.33	0.00	1.00
Metered (Dummy)	14341	0.95	0.29	0.00	2.00
PNG (Dummy)	5038	0.01	0.10	0.00	1.00
LPG (Dummy)	14851	0.85	0.35	0.00	1.00
Solid fuel (Dummy)	14851	0.52	0.50	0.00	1.00
Coal/ charcoal/ lignite cooking?	14845	0.08	0.27	0.00	1.00
Kerosene for cooking?	14845	0.07	0.25	0.00	1.00
Wealth index	14851	0.00	1.82	-2.78	6.22

Source: IRES conducted in 2019-20

Notes: Sample size is 14851.

Table 4.6. Summary Statistics for India - Urban

	Obs	Mean	SD	Minimum	Maximum
Any Electric Cooking	5038	0.10	0.30	0.00	1.00
Main Electric Cooking	5038	0.02	0.12	0.00	1.00
Electric coil (Dummy)	4987	0.01	0.09	0.00	1.00
Induction cookstove (Dummy)	4987	0.04	0.20	0.00	1.00
Micro-wave (Dummy)	4987	0.04	0.19	0.00	1.00
Oven/griller/toaster (Dummy)	4987	0.01	0.11	0.00	1.00
Rice cooker (Dummy)	4987	0.04	0.20	0.00	1.00
Gender (Female = 1)	5038	0.13	0.33	0.00	1.00
Education level	5038	5.00	2.03	1.00	8.00
Highest Education - Any member	5038	6.14	1.77	1.00	8.00
HH size	5038	4.81	2.16	1.00	25.00
Monthly expenditure (INR)	4253	10513.65	6512.51	1000.00	100000.00
Hours of power supply in a day	4991	22.14	2.95	6.00	24.00
Informed Power cut (Dummy)	3862	0.16	0.37	0.00	1.00
Metered (Dummy)	4991	0.97	0.21	0.00	2.00
PNG (Dummy)	5038	0.01	0.10	0.00	1.00
LPG (Dummy)	5038	0.96	0.19	0.00	1.00
Solid fuel (Dummy)	5038	0.10	0.31	0.00	1.00
Kerosene for cooking	5036	0.02	0.13	0.00	1.00
Wealth index	5038	1.24	1.84	-2.78	6.22

Source: IRES conducted in 2019-20

Notes: Sample size is 5038.

Table 4.7. Summary Statistics - Rural

	Obs	Mean	SD	Minimum	Maximum
Any Electric Cooking	9813	0.03	0.16	0.00	1.00
Main Electric Cooking	9813	0.00	0.07	0.00	1.00
Electric coil (Dummy)	9417	0.01	0.08	0.00	1.00
Induction cookstove (Dummy)	9417	0.01	0.12	0.00	1.00
Micro-wave (Dummy)	9417	0.00	0.05	0.00	1.00
Oven/griller/toaster (Dummy)	9417	0.00	0.04	0.00	1.00
Rice cooker (Dummy)	9417	0.01	0.09	0.00	1.00
Gender (Female = 1)	9813	0.09	0.29	0.00	1.00
Education level (Categories)	9813	4.02	1.99	1.00	8.00
Highest Education - Any member	9813	5.35	1.85	1.00	8.00
HH size	9813	5.17	2.27	1.00	25.00
Monthly expenditure (INR)	8206	6965.07	4209.36	1000.00	50000.00
Hours of power supply in a day	9351	19.70	4.31	6.00	24.00
Informed power cut (Dummy)	8437	0.11	0.31	0.00	1.00
Metered (Dummy)	9350	0.94	0.33	0.00	2.00
PNG (Dummy)	0	.	.	.	.
LPG (Dummy)	9813	0.80	0.40	0.00	1.00
Solid fuel (Dummy)	9813	0.73	0.44	0.00	1.00
Kerosene for cooking	9809	0.09	0.29	0.00	1.00
Wealth index	9813	-0.63	1.45	-2.78	6.22

Source: IRES conducted in 2019-20

Notes: Sample size is 9813.

Table 4.8. Summary Statistics for Nepal - Whole Sample

	Obs	Mean	SD	Minimum	Maximum
Number of Rice cookers	5776	0.19	0.40	0.00	2.00
Number of Microwaves	5776	0.01	0.10	0.00	1.00
Number of Electric Kettles	5776	0.08	0.29	0.00	5.00
Any LPG Cooking	6000	0.39	0.49	0.00	1.00
Any Biomass Cooking	6000	0.61	0.49	0.00	1.00
Any Charcoal Cooking	6000	0.00	0.05	0.00	1.00
Urban	6000	0.55	0.50	0.00	1.00
Log of Consumption per capita	5977	8.70	0.70	6.17	12.59
HH has a flushtoilet	6000	0.81	0.39	0.00	1.00
Do you own this Dwelling?	6000	1.00	0.06	0.00	1.00
Anyone in HH having bank account	6000	0.63	0.48	0.00	1.00
HH can get credit	6000	0.98	0.13	0.00	1.00
HH has electric meter	3915	1.00	0.00	1.00	1.00
HH has shared electric meter	3915	0.15	0.35	0.00	1.00
HH size	6000	4.61	2.05	1.00	31.00
HH Head Age	5991	49.33	13.96	19.00	96.00
HH Head Gender: Female	5991	0.20	0.40	0.00	1.00
HH Head education (categories)	3655	2.99	1.12	2.00	7.00
HH Head years of education	3655	7.98	3.67	0.00	19.00
Highest education in HH (categories)	5649	3.64	1.28	2.00	7.00
Highest years of education in HH	5649	10.13	3.45	0.00	20.00
Women's mobility measure	6000	1.88	1.20	0.00	3.00
Part of women's groups	6000	0.99	0.09	0.00	1.00
Woman has own bank account	6000	0.43	0.50	0.00	1.00
Connected to National Grid	6000	0.67	0.47	0.00	1.00
Receives information on load shedding	4047	0.12	0.33	0.00	1.00
Hrs of electricity available each day	4043	21.97	2.86	7.00	24.00
Number of outages in a week	3910	6.93	9.33	0.00	88.00
Hours of outages in a week	2953	6.87	10.65	0.08	105.00
Quality of electricity is same all year	4047	0.38	0.49	0.00	1.00
Do you own this Dwelling?	6000	1.00	0.06	0.00	1.00
Has goodwall	6000	0.39	0.49	0.00	1.00
Has goodroof	6000	0.76	0.43	0.00	1.00
HH has a flushtoilet	6000	0.81	0.39	0.00	1.00
Wealth/asset index	6000	0.00	1.81	-4.07	5.22

Source: MTF conducted between 2016 to 2018

Notes: Sample size is 6000.

Table 4.9. Summary Statistics for Nepal- Urban

	Obs	Mean	SD	Minimum	Maximum
Number of Rice cookers	3200	0.28	0.46	0.00	2.00
Number of Microwaves	3200	0.02	0.13	0.00	1.00
Number of Electric Kettles	3200	0.13	0.36	0.00	5.00
Any LPG Cooking	3285	0.55	0.50	0.00	1.00
Any Biomass Cooking	3285	0.47	0.50	0.00	1.00
Any Charcoal Cooking	3285	0.00	0.05	0.00	1.00
Urban	3285	1.00	0.00	1.00	1.00
Log of Consumption per capita	3276	8.80	0.71	6.39	12.31
HH has a flushtoilet	3285	0.84	0.37	0.00	1.00
Do you own this Dwelling?	3285	0.99	0.08	0.00	1.00
Anyone in HH having bank account	3285	0.72	0.45	0.00	1.00
HH can get credit	3285	0.98	0.14	0.00	1.00
HH has electric meter	2611	1.00	0.00	1.00	1.00
HH has shared electric meter	2611	0.16	0.36	0.00	1.00
HH size	3285	4.52	1.99	1.00	31.00
HH Head Age	3281	49.55	13.70	19.00	92.00
HH Head Gender: Female	3281	0.22	0.41	0.00	1.00
HH Head education (categories)	2214	3.11	1.19	2.00	7.00
HH Head years of education	2214	8.43	3.70	1.00	19.00
Highest education in HH (categories)	3131	3.88	1.35	2.00	7.00
Highest years of education in HH	3131	10.81	3.37	0.00	20.00
Women's mobility measure	3285	1.91	1.21	0.00	3.00
Part of women's groups	3285	0.99	0.07	0.00	1.00
Woman has own bank account	3285	0.50	0.50	0.00	1.00
Connected to National Grid	3285	0.82	0.38	0.00	1.00
Receives information on load shedding	2696	0.15	0.36	0.00	1.00
Hrs of electricity available each day	2693	22.14	2.96	7.00	24.00
Number of outages in a week	2586	6.63	9.71	0.00	88.00
Hours of outages in a week	1911	5.91	10.53	0.08	105.00
Quality of electricity is same all year	2696	0.37	0.48	0.00	1.00
Do you own this Dwelling?	3285	0.99	0.08	0.00	1.00
Has goodwall	3285	0.52	0.50	0.00	1.00
Has goodroof	3285	0.84	0.37	0.00	1.00
HH has a flushtoilet	3285	0.84	0.37	0.00	1.00
Wealth/asset index	3285	0.61	1.88	-3.72	5.22

Source: MTF conducted between 2016 to 2018

Notes: Sample size is 3285.

Table 4.10. Summary Statistics for Nepal - Rural

	Obs	Mean	SD	Minimum	Maximum
Number of Rice cookers	2576	0.08	0.27	0.00	2.00
Number of Microwaves	2576	0.00	0.03	0.00	1.00
Number of Electric Kettles	2576	0.02	0.15	0.00	2.00
Any LPG Cooking	2715	0.20	0.40	0.00	1.00
Any Biomass Cooking	2715	0.78	0.42	0.00	1.00
Any Charcoal Cooking	2715	0.00	0.05	0.00	1.00
Urban	2715	0.00	0.00	0.00	0.00
Log of Consumption per capita	2701	8.57	0.68	6.17	12.59
HH has a flushtoilet	2715	0.78	0.42	0.00	1.00
Do you own this Dwelling?	2715	1.00	0.04	0.00	1.00
Anyone in HH having bank account	2715	0.52	0.50	0.00	1.00
HH can get credit	2715	0.99	0.11	0.00	1.00
HH has electric meter	1304	1.00	0.00	1.00	1.00
HH has shared electric meter	1304	0.13	0.33	0.00	1.00
HH size	2715	4.72	2.12	1.00	20.00
HH Head Age	2710	49.07	14.28	19.00	96.00
HH Head Gender: Female	2710	0.17	0.38	0.00	1.00
HH Head education (categories)	1441	2.79	0.97	2.00	7.00
HH Head years of education	1441	7.30	3.50	0.00	18.00
Highest education in HH (categories)	2518	3.35	1.11	2.00	7.00
Highest years of education in HH	2518	9.28	3.36	0.00	18.00
Women's mobility measure	2715	1.85	1.19	0.00	3.00
Part of women's groups	2715	0.99	0.11	0.00	1.00
Woman has own bank account	2715	0.35	0.48	0.00	1.00
Connected to National Grid	2715	0.50	0.50	0.00	1.00
Receives information on load shedding	1351	0.06	0.23	0.00	1.00
Hrs of electricity available each day	1350	21.64	2.63	9.00	24.00
Number of outages in a week	1324	7.52	8.52	0.00	65.00
Hours of outages in a week	1042	8.63	10.65	0.08	98.00
Quality of electricity is same all year	1351	0.41	0.49	0.00	1.00
Do you own this Dwelling?	2715	1.00	0.04	0.00	1.00
Has goodwall	2715	0.23	0.42	0.00	1.00
Has goodroof	2715	0.66	0.47	0.00	1.00
HH has a flushtoilet	2715	0.78	0.42	0.00	1.00
Wealth/asset index	2715	-0.73	1.41	-4.07	4.64

Source: MTF conducted between 2016 to 2018

Notes: Sample size is 2715.

Table 4.11. Summary Statistics for Myanmar - Whole Sample

	Obs	Mean	SD	Minimum	Maximum
Main Electric Cooking	3383	0.22	0.42	0.00	1.00
Any Electric Cooking	3383	0.24	0.43	0.00	1.00
Rice cooker for cooking	3446	0.29	0.45	0.00	1.00
Electric kettle for boiling water	3446	0.20	0.40	0.00	1.00
Any electric appliance	3446	0.30	0.46	0.00	1.00
Any LPG Cooking	3383	0.02	0.15	0.00	1.00
Any Biomass Cooking	3383	0.59	0.49	0.00	1.00
Any Charcoal Cooking	3383	0.16	0.36	0.00	1.00
Urban	3446	0.26	0.44	0.00	1.00
Log of Consumption per capita	3446	10.61	0.87	-4.61	15.67
HH size	3446	4.57	1.96	1.00	18.00
Electricity is expensive for cooking	3446	0.34	0.47	0.00	1.00
LPG is expensive for cooking	3446	0.43	0.49	0.00	1.00
Firewood is hard to obtain	3446	0.60	0.49	0.00	1.00
Anyone in HH having bank account	3446	0.07	0.25	0.00	1.00
HH can get credit	3446	0.67	0.47	0.00	1.00
HH has electric meter	2297	0.88	0.33	0.00	1.00
HH has shared electric meter	1871	0.04	0.19	0.00	1.00
HH Head Age	3444	50.66	14.45	18.00	100.00
HH Head Gender: Female	3444	0.18	0.39	0.00	1.00
HH Head education (categories)	3444	1.81	1.35	0.00	5.00
Highest education in HH (categories)	3446	2.87	1.35	0.00	5.00
Women's Mobility measure	3446	2.34	1.07	0.00	3.00
Part of women's groups	3446	0.06	0.25	0.00	1.00
Woman has own bank account	3446	0.02	0.14	0.00	1.00
Connected to National Grid	3446	0.39	0.49	0.00	1.00
Connected to Minigrid	3446	0.08	0.28	0.00	1.00
No grid connection	3446	0.53	0.50	0.00	1.00
Receives information on load shedding	2516	0.21	0.41	0.00	1.00
Hrs of electricity available each day	2501	19.70	7.40	0.00	24.00
Number of outages in a week	2098	3.29	5.13	0.00	88.00
Hours of outages in a week	2029	6.19	15.79	0.00	120.00
Quality of electricity is same all year	2516	0.72	0.45	0.00	1.00
Do you own this Dwelling?	3446	0.90	0.30	0.00	1.00
Has goodwall	3446	0.21	0.41	0.00	1.00
Has goodroof	3446	0.82	0.38	0.00	1.00
HH has a flushtoilet	3446	0.78	0.42	0.00	1.00
Normalized wealth index	3446	0.19	1.04	-2.15	5.69

Source: MTF conducted between 2016 to 2018

Notes: Sample size is 3446.

Table 4.12. Summary Statistics for Myanmar- Urban

	Obs	Mean	SD	Minimum	Maximum
Main Electric Cooking	1684	0.38	0.49	0.00	1.00
Any Electric Cooking	1684	0.42	0.49	0.00	1.00
Rice cooker for cooking	1721	0.56	0.50	0.00	1.00
Electric kettle for boiling water	1721	0.37	0.48	0.00	1.00
Any electric appliance	1721	0.58	0.49	0.00	1.00
Any LPG Cooking	1684	0.10	0.30	0.00	1.00
Any Biomass Cooking	1684	0.22	0.41	0.00	1.00
Any Charcoal Cooking	1684	0.38	0.49	0.00	1.00
Urban	1721	1.00	0.00	1.00	1.00
Log of Consumption per capita	1721	10.88	0.77	-4.61	15.67
HH size	1721	4.65	2.16	1.00	18.00
Electricity is expensive for cooking	1721	0.44	0.50	0.00	1.00
LPG is expensive for cooking	1721	0.50	0.50	0.00	1.00
Firewood is hard to obtain	1721	0.56	0.50	0.00	1.00
Anyone in HH having bank account	1721	0.12	0.32	0.00	1.00
HH can get credit	1721	0.71	0.45	0.00	1.00
HH has electric meter	1323	0.84	0.36	0.00	1.00
HH has shared electric meter	1073	0.04	0.19	0.00	1.00
HH Head Age	1720	52.19	14.47	20.00	100.00
HH Head Gender: Female	1720	0.23	0.42	0.00	1.00
HH Head education (categories)	1720	2.19	1.41	0.00	5.00
Highest education in HH (categories)	1721	3.37	1.31	0.00	5.00
Women's mobility measure	1721	2.42	1.04	0.00	3.00
Part of women's groups	1721	0.06	0.24	0.00	1.00
Woman has own bank account	1721	0.05	0.22	0.00	1.00
Connected to National Grid	1721	0.74	0.44	0.00	1.00
Connected to Minigrid	1721	0.11	0.31	0.00	1.00
No grid connection	1721	0.15	0.35	0.00	1.00
Receives information on load shedding	1468	0.19	0.40	0.00	1.00
Hrs of electricity available each day	1458	20.25	6.97	0.00	24.00
Number of outages in a week	1180	2.55	4.30	0.00	88.00
Hours of outages in a week	1143	4.76	12.32	0.00	120.00
Quality of electricity is same all year	1468	0.75	0.43	0.00	1.00
Do you own this Dwelling?	1721	0.81	0.40	0.00	1.00
Has goodwall	1721	0.41	0.49	0.00	1.00
Has goodroof	1721	0.91	0.28	0.00	1.00
HH has a flushtoilet	1721	0.82	0.39	0.00	1.00
Normalized wealth index	1721	-0.24	0.84	-2.14	3.66

Source: MTF conducted between 2016 to 2018

Notes: Sample size is 1721.

Table 4.13. Summary Statistics for Myanmar- Rural

	Obs	Mean	SD	Minimum	Maximum
Main Electric Cooking	1699	0.28	0.45	0.00	1.00
Any Electric Cooking	1699	0.32	0.47	0.00	1.00
Rice cooker for cooking	1725	0.39	0.49	0.00	1.00
Electric kettle for boiling water	1725	0.27	0.44	0.00	1.00
Any electric appliance	1725	0.40	0.49	0.00	1.00
Any LPG Cooking	1699	0.01	0.10	0.00	1.00
Any Biomass Cooking	1699	0.62	0.49	0.00	1.00
Any Charcoal Cooking	1699	0.13	0.34	0.00	1.00
Urban	1725	0.00	0.00	0.00	0.00
Log of Consumption per capita	1725	10.62	0.96	-4.61	14.41
HH size	1725	4.45	1.87	1.00	17.00
Electricity is expensive for cooking	1725	0.35	0.48	0.00	1.00
LPG is expensive for cooking	1725	0.41	0.49	0.00	1.00
Firewood is hard to obtain	1725	0.56	0.50	0.00	1.00
Anyone in HH having bank account	1725	0.05	0.23	0.00	1.00
HH can get credit	1725	0.70	0.46	0.00	1.00
HH has electric meter	974	0.84	0.37	0.00	1.00
HH has shared electric meter	798	0.07	0.25	0.00	1.00
HH Head Age	1724	51.02	14.22	18.00	99.00
HH Head Gender: Female	1724	0.20	0.40	0.00	1.00
HH Head education (categories)	1724	1.78	1.32	0.00	5.00
Highest education in HH (categories)	1725	2.87	1.31	0.00	5.00
Women's mobility measure	1725	2.41	1.01	0.00	3.00
Part of women's groups	1725	0.07	0.25	0.00	1.00
Woman has own bank account	1725	0.02	0.13	0.00	1.00
Connected to National Grid	1725	0.55	0.50	0.00	1.00
Connected to Minigrid	1725	0.05	0.22	0.00	1.00
No grid connection	1725	0.39	0.49	0.00	1.00
Hrs of electricity available each day	1043	21.27	5.52	1.00	24.00
Number of outages in a week	918	4.10	5.58	0.00	35.00
Hours of outages in a week	886	7.04	15.41	0.00	120.00
Quality of electricity is same all year	1048	0.71	0.45	0.00	1.00
Do you own this Dwelling?	1725	0.90	0.30	0.00	1.00
Has goodwall	1725	0.20	0.40	0.00	1.00
Has goodroof	1725	0.86	0.35	0.00	1.00
HH has a flushtoilet	1725	0.78	0.41	0.00	1.00
Normalized wealth index	1725	0.24	1.09	-2.15	5.69

Source: MTF conducted between 2016 to 2018

Notes: Sample size is 1725.

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