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Essays in Public Finance and Environmental Economics

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Economics

by

Radhika Goyal

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2023

The Dissertation of Radhika Goyal is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

University of California San Diego

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DEDICATION

To maa and paa

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ABSTRACT OF THE DISSERTATION

Essays in Public Finance and Environmental Economics

by

Radhika Goyal

Doctor of Philosophy in Economics

University of California San Diego, 2023

Professor Samuel Bazzi, Co-Chair
Professor Tom Saul Vogl, Co-Chair

This dissertation focuses on topics concerning public finance, state capacity, and the environment.

In the first chapter, we study the role of proximity to administrative power in explaining spatial inequality in access to public goods. Using a natural experiment in India that quadrupled the number of sub-districts (the lowest level of administrative jurisdiction), we explore the impact of redistribution of political power on spatial inequality of public good investment. By analyzing digitized high-resolution data encompassing approximately 10,000 villages spanning over 55 years, we demonstrate that reducing the distance to local

government headquarters helps in bridging the gap in the provision of essential public amenities for remote villages, and furthermore, yields evidence of long-term improvements in state capacity.

In the second chapter, we focus on turning points in tax collection. Our method detects both sustained accelerations and decelerations of tax collection (relative to GDP) in a global and historical sample of 150 countries since 1965. Turning points are prevalent (238 events in total), persistent for at least 15 years in many cases, and occur more frequently at lower levels of the country's development. We show that changes in the political environment are strong statistical predictors of accelerations, tax reforms, and economic changes less so. Decelerations appear more unpredictable than accelerations.

In the third chapter, we study the ecological gains of place-based environmental measures to ramp up conservation efforts. By combining geo-referenced Indian village maps overlaid with digitized protected area maps and a fuzzy regression discontinuity design, we find that protected areas help improve forest cover. Villages located within protected areas also experienced improved economic activity, attributed in part to the growth of the tourism sector, particularly in wildlife sanctuaries. Moreover, our findings suggest that states which allocate a higher share of expenditure to the forestry sector exhibit stronger forest conservation outcomes.

Chapter 1

Redistributing Administrative Power to Bridge Spatial Inequality

1.1 Introduction

Spatial inequality has emerged as a significant concern in economic research and policy discussions. Geographic inequality encompasses disparities in the availability of education, healthcare, infrastructure, and other basic services (Krugman (1999), Gallup, Sachs, and Mellinger (1999), Kanbur and Venables (2005)) which can lead to disparities in access to essential services and economic opportunities (Henderson (1999), Galster and Sharkey (2017), Chyn and Katz (2021)). These inequalities can perpetuate cycles of poverty, hinder social mobility, and exacerbate existing inequalities within and between regions (Chetty et al. (2014), Corak (2013)). However, the scarcity of high-resolution data on government spending has hindered efforts to study the spatial inequality of government investment in developing countries. In this paper, we study policies that can improve this spatial variation of government investment in public goods and services in the context of Indian villages.

To examine the presence of spatial inequality in public good provision, we gathered high-resolution granular data for over 10000 villages in the Indian state of Telangana (erstwhile part of Andhra Pradesh) spanning a period of roughly 59 years. In addition to manually digitized historical records on demographics and access to public amenities, we obtained disaggregated official records on public works participation as well as the amount of compensation paid. We also obtained detailed agriculture census data including plot level area by crop-type as well as village irrigation facilities; and public and bureaucrat attendance data for village council meetings. This allows us to document spatial inequality in government investment and engagement in our context.

We exploit a policy change in the state of Andhra Pradesh which quadrupled the number of sub-districts (the lowest level of administrative jurisdiction) in 1985. Given the policy reform happened at the state level, the entire population is impacted by the policy experiment. We thus focus on the distributional impacts of differential change in distance to local government headquarters from the village. We use a match pair strategy where we focus on neighboring village pairs in the same old subdistrict but following the split, now at different distances to their respective local sub-district headquarters. Using descriptive and empirical validation checks we argue that this policy provides an exogenous source of variation in the change in distance of a village to its local government headquarters, allowing us to study the role played by proximity to political power on spatial improvement in state capacity.

Interestingly, we find an immediate improvement in access to government investment, especially for originally distant villages. Villages that were brought closer to their new government headquarter had improved access to public goods within five years of the policy. While access to public amenities that fall within the mandate of the subdistricts such as primary schools, maternity facilities, irrigation networks, and dirt roads improve; no differential impact on larger public goods, such as electricity access and paved tar roads, controlled by the state governments is found. This is because these boundaries create a discontinuity in local government presence while other state-level amenities vary smoothly across borders. While people, goods, and firms can move across the internal administrative boundary with relative ease, the local government (in the form of sub-district administrators) are unlikely to cross it, thus creating a sharp discontinuity of government presence at the sub-district border.

We also find significant second-stage impacts on outcomes like adult literacy and movement out of agriculture highlighting the role of government investment in public welfare. We find that reducing distance to public headquarters increases access to bureaucrats as measured by attendance by bureaucrats at village meetings even 35 years after the policy.

This paper contributes to a few strands of literatures. First, the project relates to the state capacity literature. State capacity has emerged as a crucial topic in discussions surrounding democracy, service delivery, and public finance. Extensive research over the past few decades has explored various constraints that impede the state's ability to provide public goods, including issues related to accountability, incentives, representativeness, and the effectiveness of political leaders (Pande (2011); Ferraz and Finan (2011); Fisman, Schulz, and Vig (2014)). In this paper, we study the proximity to administration as a constraint to public good delivery. Asher, Nagpal, and Novosad (n.d.) study a similar question of geography of administration; in this project however, we use a natural experiment to directly study the impact of changes in proximity. State capacity improvements often require long-term investments, this paper thus highlights a quick actionable policy to improve equitable access to government investment.

The second strand of literature this project relates to is the decentralization literature. The decentralization literature focuses on the trade-off between tailoring and monitoring of public goods to local needs vs local elite capture (see Bardhan and Mookherjee (2005) for a review on the theoretical and empirical literature on decentralization). The policy reform we study has the spirit of decentralization as it increases access to government thereby increasing proximity to administration but retains the administrative structure (there was no change in responsibilities across different tiers of the government).

The paper also contributes to the administrative unit proliferation literature. Several studies have documented the impact of splits or consolidation on economic and environmental outcomes or impact of political alignment (Grossman and Lewis (2014); Bazzi and Gudgeon (2021); Burgess et al. (2012)). The underlying forces at play while deciding the size of administrative jurisdiction literature are economies of scale and accommodating heterogeneity in preferences at the national level (Alesina and Spolaore (1997); Alesina, Spolaore, and Wacziarg (2000); Bolton and Roland (1997)) and sub-national governments (Coate and Knight (2007)). The natural experiment we use has the spirit of the same administrative unit proliferation. However, instead of studying the average impact of the policy, we provide evidence for a significant channel through which efficient service delivery can work: physical distance to administration. We use high-resolution village-level data that allows us to study the question of state capacity in terms of proximity to the government. Our results show that smaller administrative units can help improve the delivery of public services in our context and therefore enhance state capacity in developing countries.

The final strand of literature that this project directly speaks to is the economic geography literature. Gravity models have documented the negative impact of distance between locations on economic outcomes like migration, poverty, and structural transformation (Atkin and Donaldson (2015); Fafchamps and Wahba (2006); Michaels, Rauch, and Redding (2012); Storeygard (2016)). We study geographic proximity between government headquarters and a village, showing greater distance to local governments reduces rural access to public services, further exacerbating spatial inequality.

Redefining administrative boundaries remains a pertinent policy experiment, particularly in addressing the disproportionate impact of weak state provision of core public goods on the poor and marginalized, who heavily rely on public services and welfare programs. This widespread practice in public administration holds the potential for enhancing public good provision by reducing costs, streamlining oversight, improved understanding of local needs, increased governance incentives, and diminished community organizing expenses, ultimately fostering proximity to power and government investment.

The rest of the paper is organized as follows. In Section 1.2, we discuss the context and its relevance. Then, in Section 1.3 we describe the multiple data sources and explain the construction of our main variables. Section 1.4 outlines our empirical strategies. Section 1.5 details the key results, and Section 1.6 concludes.

1.2 Contextual Background

In India, the public administration system operates across multiple tiers. At the highest level, the federal government assumes responsibility for national public goods. Collaborating with the federal government, the state governments play a crucial role in implementing social and anti-poverty programs. Additionally, the states are further divided into districts, which bear the responsibility of executing both federal and state government initiatives within their respective territories. Subsequently, there are sub-districts, known as mandals or taluks, which encompass numerous villages and a few towns. These sub-districts play a crucial role in service delivery, revenue collection, and even conduct elections for key positions. The focus of this paper revolves around this level of government.

This project focuses on villages in Telangana (erstwhile Andhra Pradesh).[1] Andhra Pradesh was one of the two states in the country to initiate a democratic decentralization process on the lines of the national Balawanta Rai Mehata Committee Report in 1959. In pursuit of bringing administration closer to the people, the state introduced the concept of mandals.[2] The notable changes included reducing the size of sub-districts, known as Mandal Praja Parishads, and creating more units, approximately three to four Mandal Praja Parishads for each original Taluk Panchayat Samithies. This led to the abolition of 330 Panchayat Samithies and the establishment of 1,104 Mandal Praja Parishads in their place. Prior to 1985, the average population of a sub-district ranged from 130,000 to

[1]Telangana was split from the state of Andhra Pradesh in 2014.

[2]Vaddiraju (2020) discuss political objectives of the move towards greater decentralization and splitting of districts.

250,000 citizens, with 90-160 villages encompassed within each. The key responsibilities of mandal administrators encompass various areas, including facilitating access to welfare programs, managing approvals and licenses, maintaining and establishing primary health facilities, schools, rooads, as well as providing extension services such as agriculture support.

Andhra Pradesh offers a suitable context for this study. It is fairly representative of Indian states: in 2011 (last population census in our study sample), it ranked as the fifth most populous state in India and had a rural population exceeding 70 percent. In terms of human development indicators such as gross enrollment in primary school, literacy rates, and infant mortality, as well as service delivery metrics like teacher absenteeism, it closely approximated the all-India average. Moreover, it was the largest state to implement the recommendations of the national Ashok Mehta Committee (1977), which called for the establishment of smaller intermediate-tier Mandal Panchayats situated in close proximity to villages. The policy changes in Andhra Pradesh were notably significant, with a quadrupling of its subdistricts within a year. Additionally, these subdistricts (mandals) serve as an ideal level of local government to examine in this study, given their responsibilities encompassing both revenue and administrative services, as discussed earlier.

The objective behind the change was to foster a more efficient administration by promoting proximity to power. The goal was to enhance participation, particularly in the implementation of various government welfare measures, with a particular focus on the marginalized segments of society. It was anticipated that this shift would lead to increased responsiveness in government activities and welfare programs by catering to smaller populations, typically ranging from 35,000 to 55,000 individuals (in 1980s). Although the elected heads of the new administrative units (mandals) were endowed with the same powers as their predecessors (taluks), their responsibilities expanded to encompass broader development efforts (Government of Andhra Pradesh (1985)). The overarching objective was to bring the administration closer to the people and ensure easy accessibility to all public services.

1.3 Data

To study spatial inequality and the role of geography, we combine several sources of administrative village-level data. In the next few subsections, we discuss each component in greater detail.

Population Census

We manually digitized village-level data from the Population Census 1961-2011, which reports demographic characteristics such as population, literacy rate, and the share of village population that belongs to marginalized communities including Scheduled Castes (SC) and Scheduled Tribes (ST). We also use information on the availability of various amenities such as schools, health centers, water facilities, electricity, post offices, roads, and irrigation facilities in the village. Finally, we also digitize information on labor market employment by gender. The key set of outcomes will include village-level access to services (schools, maternity homes, electricity, water, dirt roads) which are executed by Mandal officers.

Public Works Data

India's National Rural Employment Guarantee Scheme is a landmark effort to redistribute income to the rural poor. Mandal officers act as program officers for public works scheme NREGS and they are in-charge of monitoring and supervising the implementation of works in addition to releasing funds. While NREGS was aimed at marginalized areas, given it is an untargeted program and had minimal administrative spillovers to neighboring villages in other mandals, it is the perfect program for this study. Both the type of projects approved and the release of funds (and possible leakages found in Muralidharan, Niehaus, and Sukhtankar (2016)) speak directly to the question of the implementation of welfare programs. In order to document differences in quality of service provision we use public works (NREGS) estimates on assets approved, number of workers, and amount disbursed as key outcome variables available at the beneficiary level (2005-2020).

Agriculture Census

We include village-level data on land holdings which are marginal, small, small-medium, medium, and large. As per the agricultural census, the size of the land holding is defined as follows: marginal (less than 1 hectare), small (between 1 & 2 hectares), small-medium (between 2 & 4 hectares), medium (between 4 & 10 hectares), large (more than 10 hectares). In addition, we obtained data on the area cropped and irrigated for each village from the Rural Development department.

Socio Economic and Caste Census

In 2012, the Government of India conducted the Socioeconomic and Caste Census (SECC), a one-off census of all households in the country, to collect detailed information on assets, incomes, occupation structure, and demographic characteristics at the household level. This information is substantially richer than information collected during the Population Census. We use village-level average of aggregated monthly income.

Access to Banks

Information on access to banks comes from the Reserve Bank of India Commercial Bank Directory which provides details of each commercial bank branch in the country with the name of the state, district and rural center (roughly equivalent to a village) where the branch is situated. It also provides the year in which each bank branch got established among many other indicators. We use this in addition to post-office data from the census to explore the impact on financial inclusion.

Gram Panchayat Development Plan data

The GDPD provides data on the representation of each of the government line ministries in gram panchayat planning meetings. In addition, the portal provides data on attendance by gender and minority status at these gram panchayat meetings. We cluster our villages to the gram panchayat level for this analysis.

Mission Antyodaya data

To validate village-level provision of public good, we use data from the Mission Antyodaya initiative website. This initiative was established by the central government with the aim of collecting regular and comprehensive village-level data. The data also provides information on health outcomes like underweight and anemic children as well as data on beneficiaries of (national) government policies.

GIS data

GIS data on current and historic sub-district borders and headquarters were obtained from the Telangana State Remote Sensing Applications Centre. Remote sensing data are used to measure outcomes otherwise unavailable at the village level. Nightlights (NASA DMSP 1992-2013) provide a proxy for total village output and also the availability of electricity/street-lighting. We estimate nightlights at the level of village using methodology from Asher, Lunt, et al. (2021). We also use include village forest cover data VCF for years 2000-2013. Finally, we overlay river and altitude maps to study breaks in geographical controls.

Costing information

Information on salaries for local government (mandal) public servants in 1986 and 2019 and the total mandal establishment costs were obtained from state budget archives and the Telangana Panchayati Raj department.

1.4 Empirical Strategy

Studying the role of distance and government spending comes with two central challenges: measurement and causality. The empirical strategy overcomes these challenges by using change in distance to administrative headquarters for neighbouring villages across internal administrative boundaries to obtain exogenous variation in state capacity.

This section develops our empirical strategy in three steps. First, we document the spatial inequality in public good provision. Second, we describe the baseline estimating equations for identifying the impact of change in distance for neighboring villages that were separated into new subdistricts. Third, we detail the framework for estimating heterogeneous effects based on the original distance to headquarters before policy reform.

Before we study the role played by reducing distance to local government headquarters, it's important to document spatial inequality in public good provision. The traditional optimal size of jurisdiction literature assumes homogeneous service delivery within the administrative boundary. This hypothesis is challenged in our setting as evidenced by Figures 1.1-1.2 as well as Appendix Figures 1.A.1-1.A.2. Here we provide a geographical representation of access to a public facility (schools, hospitals, electricity, and drinking water) against distance to local government headquarters in 1981 (before the policy reform). The negative gradient suggests that before the policy change, access to public goods was negatively correlated with distance to headquarters. Further, in Figure 1.3 we highlight the change in access to public schools from 1961 to 1981. While the slope is negative for both decades which highlights large spatial inequality of even basic public goods within the smallest administrative unit, there is evidence of some catch-up by the most distant villages. This inequality could be population and historical differences. We use a natural experiment to study how policy change can impact this spatial inequality.

Figure 1.4 illustrates the mean change in distance of a village to its new administrative headquarters (Appendix Figure 1.A.3 does so for the village in the 90th percentile).

The average distance was reduced by 9.1 kilometeres, ie, by more than half, highlighting the scale of the policy experiment. However, this change in distance was experienced by nearly the entire state (Appendix Figure 1.A.4 displays the heterogeneity in impact). Thus, our empirical strategy focuses on using villages originally in the same subdistrict but on either side of the new subdistrict boundaries. If the villages are sufficiently similar on observable characteristics, we can say that the only difference that remains between the two types of villages is that they lie in different jurisdictions post-1985 and thus, differ in their distance to their new subdistrict headquarters. These boundaries create a discontinuity in local government presence while other observable and unobservable confounders should vary smoothly across borders. Hence, we can view villages near the border as subjected to a natural experiment, in which they are randomly assigned to different sub-district mandal-level institutions, and in particular, to different the magnitude of effective state capacity.

We illustrate the main match-pair empirical strategy in Figure 1.5. The central idea of the identification strategy is to compare villages on either side of mandal boundaries (that were previously in the same administrative subdistrict (Taluk) unit in 1985 and are now close to the new subdistrict (Mandal) boundaries and use distance to the new subdistrict headquarters as a measure of government presence. The figure focuses on one subdistrict prior to policy change (black boundary). The subdistrict was subdivided into four subdistricts in 1985 marked by white boundaries. Each small blue polygon is a village in the study sample. The orange and yellow dots represent the original and new subdistrict headquarters respectively. We pick two villages (highlighted in yellow) that were originally in the same subdistrict and almost equidistant to the old subdistrict headquarters (orange dot), but post-1985 they were placed in different subdistricts and thus have a differing distance to their new headquarters. Our identifying variation thus comes from a change in administrative remoteness along the same subdistrict border.

We create these match-pairs by first restricting the sample to villages within 10km of the new subdistrict borders. We then run a propensity score match for pairs within the same original old subdistricts using linear distance to the original capital, village population (pre-split), and log area. We restricted village pairs to a pairwise distance of less than 20 kilometers. This gave us a sample of the final matched pairs that were in the same subdistricts pre-1985 but were in different subdistricts post-split, and were similar in baseline characteristics pre-split. We get roughly 5500 match-pairs using this strategy. We further run robustness checks with match-pairs that share a village boundary. Our key estimation equation for this match-pair design is:

$$\triangle y_{v,p} = \alpha + \beta \triangle Dis_{v,p} + \theta_p + \epsilon_{v,p} \tag{1.1}$$

where v is village, p is the village match-pair. These outcomes include access to different types of public goods and rural economic indicators, as described in Section 1.3. $Dis_{v,p}$ refers to log distance of village v in village-pair p to its sub-district HQ (so $\triangle Dis_{v,p}$ refers to reduction in log distance of village v to its sub-district HQ). We include village match-pair fixed effects and bootstrap standard errors.

The next strategy extends a spatial regression discontinuity design (see Dell (2010)) which measures the local treatment effect at a geographic boundary that splits observations into treated and control areas. Here we do not split the sample into treatment and control and instead focus on change in distance to new subdistrict boundary as a continuous variable. Our estimation equation is:

$$\triangle y_{v,m,s,t} = \alpha_0 + \beta \triangle Dis_{v,s,m} + \delta X_{v,m,s,t} + \psi_b + \theta_s + \epsilon_{v,m,s,t} \tag{1.2}$$

where $\triangle y_{v,m,s,t}$ is the change in outcome of interest for village v in new subdistrict m (part of old subdistrict s) in time t. $\triangle Dis_{v,s,m}$ is our key variable of interest. We also estimate the coefficient of interest, β, non-parametrically by distance to old HQ.

We control for a vector of geographic and demographic controls $X_{v,m,s,t}$. Geographic controls include mean elevation in the village and the village's distance to a major river. Demographic controls include population in 1981, the proportion of marginalized communities (percentage of village population in 1981 that belonged to Scheduled Castes (SC) or Scheduled Tribes (ST)), and area of the village.

To ensure that our comparisons are within neighboring villages, we create equally-spaced segments along the new subdistrict borders. ψ_b is the boundary segment closest to a village. In this case, we pick each boundary segment of about 10 kilometers (but do test robustness for 5 and 20 kilometers as well). θ_s is the new subdistrict fixed effect. This controls for any subdistrict-specific factors that may affect rural economic outcomes or the provision of public goods. The inclusion of these fixed effects ensures that the coefficient of interest, captures the effect of reduction in distance that is over and above any subdistrict-wide average governance measure.

We restrict the analysis to villages within five kilometers of the new boundary segment but do check robustness for 2 and 7 kilometers (all villages in the sample have a new boundary segment within 10 kilometer distance). Finally, $\epsilon_{v,m,s,t}$ is the error term. We cluster the standard errors at the subdistrict-segment level, since this is the level of treatment in our analysis (following Abadie et al. (2023)). We further check if the results are robust to allowing spatial correlation in the standard errors.

We focus on basic public goods and welfare programs for outcomes $\triangle y_{v,m,s,t}$, preferences for which are relatively homogeneous. We also need to ensure there is no sorting that makes observations on both sides of the border incomparable. We only have district-level migration data so can not check for differential sorting. Instead, we test for village-level population growth and changes in fertility (using data on the population of 0-6 aged children) in the periods after the policy change.

The identification strategy also relies on the assumption that comparison villages have similar access to other (non-public) facilities and amenities. If this is not the case, the outcomes will be driven by a combination of distance to administration and distance to markets, and it would not be accurate to attribute them to administrative remoteness alone. While people, goods, and firms can move across this internal administrative boundary with relative ease, the local government (in the form of mandal administrators) are unlikely to cross it, thus creating a sharp discontinuity of government presence at the sub-district border.[3]

Finally, the validity of our design requires a number of key assumptions about the placement of the subdistrict boundaries and headquarters. Our claim that these sub-district boundaries were largely quasi-random follows a three-prong reasoning. First, the policy change was rapidly implemented. The state government that came into power in 1981 implemented the policy within three years. There was no suggested budget for the creation of these new mandals in the estimates for 1984 and 1985 and only appear in the revised estimates for 1985 in the 1986 budget documents. Second, the Delimitation Commission which is typically responsible for using population census data to redraw boundaries was not in place in the time period of the study. Anecdotally, we spoke to a number of policymakers who suggested that the government's key objective was to ensure that all villages were less than 25 kilometers from their new government headquarters and there were little other considerations while choosing boundaries. Finally, we check for differential trends in pre-existing demographic variables and key outcomes (provision of primary schools, medical facilities, irrigation facilities, etc).

Choice of new sub-district headquarters is, however, more likely to be endogenous as these headquarters are typically placed in large towns or cities. However, because we focus on differential change in distance to subdistrict headquarters for neighboring villages so this is not a concern for our identification strategy. For robustness, we use a combination of alternative placebo headquarters using other large towns in the new subdistricts that could have been the new headquarters.

[3] Researchers have argued that local governments have clear and legally recognized geographic boundaries over which they exercise authority and within which they perform public functions (Rondinelli et al. (1983)).

A key caveat to the above approach includes that we do not have access to official public employment records. The marginal new public sector administrator might be of a significantly lower quality or have different electoral incentives post-split. Thus, in our heterogeneity impact, we also focus on villages on the same side of the new boundary and catered to by the same subdistrict government. We compare outcomes of these villages by different bands of distance to original headquarters. This allows us to control for new subdistrict-level changes like changes in administrative quality and electoral outcomes.

Descriptive Statistics. Table 1.1 provides the descriptive statistics focusing on village data pre-reform in 1981. While there are over 10000 villages in the sample, fuzzy matching and multiple rounds of manual merging gave us a final sample of about 9770 villages across all datasets. Average population size of these villages is about 1500 people with a third of the population comprising of marginalized communities. Literacy levels in 1981 were pretty low with only 23% of the population was literate on average. Access to services like public primary schools within 5 kilometers and drinking water was pretty universal but other facilities like medical facilities were rare.

Balance Tests. To ensure the validity of the identification strategy, we verify that the change in distance ($\triangle Dis_{v,m,s}$) to headquarters was uncorrelated with village-level demographics and amenities. These results are captured in Tables 1.2-1.3. We regress pre-reform demographics like village population, the proportion of marginalized communities, and literate population on change in distance to new subdistrict headquarters. In addition, we test for differences in altitude and distance to water bodies to test for breaks in geographical outcomes. Overall, the changes in distances are not correlated with demographic and geographic variables. We also test for differences in access to public goods: a primary school within 5 kilometers of the villages, access to dirt roads, access to maternity homes within 5 kilometers, access to drinking water, and proportion of land with access to irrigation services. Roughly 80% of the households are agricultural, thus irrigation access is a key outcome of interest. Changes in distance to villages seem to be uncorrelated with pre-reform access to amenities and public good service delivery.

Pre-Trends. Next, we identify parallel pre-trends in access to amenities and public good service delivery before the split. We capture these in Table 1.4 which present pre-split changes in access to public goods. We find no difference in growth pre-split. Event study specifications in Figure 1.6 also show that pre-trends are largely flat and no discernible difference is found.

1.5 Results

In this section, we first discuss the event study plots in Figure 1.6 where we plot access to public goods before and after the policy change. Next, we highlight the main impacts in 1991- five years after policy change, and the impacts on public good provision from the 2011 census - roughly 25 years after the reform. We also study impacts on the public works program in 2015 and civic engagement data in 2020 - nearly 30-25 years after the reform. Finally, we check for robustness using alternate empirical strategies discussed above.

Event study. Figure 1.6 plots how access to public goods and amenities evolved with a change in distance to subdistrict headquarters before and after the policy. Relative to the year 1981 (five years prior to the split), access to public goods pre-split was not correlated with the change in distance of the match-pair villages. This aligns with the parallel trends results we discuss in Section 1.4. After the policy (marked by red dashed line), villages that had a larger relative reduction in distance to their respective headquarter had an immediate jump in access to public goods such as primary schools, maternity homes, dirt road, and safe drinking water. The jump is immediate and gradually dies down by the year 2011.

Next, we present the match pair results of whether a change in administrative remoteness changed the probability that a village had access to basic public goods within

5 years of the policy (in Table 1.5). Across all outcomes, reduction in distance significantly improved access to public goods like schools, post-office, health facilities, dirt roads, drinking water, and irrigation. For instance, a one-kilometer additional reduction in distance to a local government headquarter increased the probability of having a dirt road by 2.2pp. Given the average reduction in the distance to a subdistrict headquarters was close to 9.1 kilometers (as in Figure 1.4), this is a sizeable impact against a base of 0.48 which suggests distance can play a very meaningful mediating role in state capacity improvement efforts. Effect sizes are small for maternity homes but the share of villages with access to any such facility before the policy change was low thus making these differences economically meaningful. For robustness, we test these results with the second long-difference specification with the entire sample of villages in Table 1.6.

Heterogeneity by distance to original subdistrict headquarters. We disaggregate these average impacts for villages that were originally much further from their headquarters, i.e, distance to old headquarters greater than 25 kilometers. These were the villages the policy explicitly wanted to bring closer (see section 1.2). Table 1.7 presents these results where $Disold$ refers to distance to old subdistrict headquarters. Almost all of the action is driven by these very far villages ($Disold$ greater than 25 kilometers), suggesting the role of administrative headquarters in promoting equitable access to public goods. We plot these impacts non-parametrically in Figures 1.7 and 1.8 which suggests potential catch-up for very remote villages, especially those with distance larger than 40 kilometers to headquarters.

Impact on goods with large economies of scale and administered by the state or district governments. In the above discussion, we focussed on goods that are the responsibility of the subdistricts (as discussed in Section 1.2. Other public goods such as hospitals, tarr roads, and universities, have large economies of scale and are typically provided by the state government with support from the district governments. We test whether the splitting led to a differential change in access to these state-provided public goods. Table 1.8 is reassuring in that there is no significant or economically meaningful impact in any of these larger public goods.

Impact on public works. In order to better understand the long-run impacts of distance in mediating the role of state capacity reform, we use data from NREGS, the largest public works program. As discussed in Section 1.2, subdistricts are responsible for monitoring and implementation of the program. NREGS has minimal administrative spillovers to neighboring villages in other mandals making it another good state capacity reform to test in our setting. Tables 1.13, 1.14 and 1.15 present results of impact of changes in distance on NREGS outcomes in 2015 roughly 30 years post-reform. Data before 2015 is very sparsely available, and because the state was formed in 2014, we choose 2015 for this analysis. Enrolment in public works increased with a greater reduction in distance and average impacts on workdays improved for the marginalized communities (scheduled castes SC). A ten-kilometer additional reduction in distance to a local government headquarter increased the number of workers (jobcards) by 5% with the increase for scheduled caste workers a 13.2%. There is little difference in assets approved and total expenditure but significant results for the key policy outcome variable - actual disbursement into bank accounts. The results hint at some long-term persistent impacts of reduction in distance.

Impact on short-run private outcomes. Having established that reducing remoteness improves rural access to public goods, we now investigate whether it affects private labor outcomes including literacy and occupation. We see no impact on occupational outcomes in 1991 as illustrated in Table 1.11. This is partly because these are rather sticky variables, and also because economic variables like access to markets and jobs are not affected by administrative boundaries. While greater distance to administrative headquarters could reduce rural residents' access to government jobs and drive differences in the employment structure, public sector employs a very small portion of the people, and our identification comes from the change in distance for previously remote villages.

Impact on the long-term public good provision. We now test whether these impacts persist in the long-run after 25 years of policy change. There is little long-run impact on public good provision as detailed in Tables 1.9 and 1.10. Access to schools, roads, and drinking water became national priorities in the first decade of the 21st century and there is nearly universal access to such public goods in the sample. This suggests a ceiling impact of reduced remoteness on the binary outcome of the provision of public goods. However, these subdistrict governments are also responsible for the maintenance and quality of public good provision as discussed in section 1.2. We use data from the Mission Antodaya to test even longer-term impact of change in distance in 2021 (Appendix table 1.A.1). We find no difference in outcomes by distance for state-provided goods like all-weather roads, hours of electricity, piped drinking water. Villages that were brought closer continue to have a higher probability of access to a brick road even in 2021 (not captured in Tables 1.9 and 1.10 above).

Impacts on literacy are more evident in the longer-term - a one-kilometer additional reduction in distance to a local government headquarter increased literacy rate by 1.1pp 25 years later (Table 1.12 and Figure 1.9) suggesting some evidence of long-term impacts of reduced remoteness. We also test impact on nightlights - a proxy for economic well-being, but also, potentially meaningful evidence for maintenance of streetlights - and there is some evidence of impact on average nightlights.

Table 1.12 suggests that proximity to local government headquarters impacts the rural employment structure in the long run. We find that administrative proximity increases the share of village workforce engaged in non-farm activities, potentially through its effect on literacy, access to paved roads, and other public goods. Structural transformation of the economy from agriculture to other economic sectors is key to income growth in developing countries. Macrodevelement literature has documented large differences in productivity between agriculture and other sectors of the economy (Gollin, Lagakos, and Waugh (2013)). Again, impacts are small partly because economic outcomes are more fluid across administrative boundaries but we are studying this interaction of public and private outcomes with more disaggregate occupational data. There are, however, no impacts on consumption and poverty rates obtained from the socio-economic census data (Appendix Table 1.A.2).

Impact on civic engagement and bureaucratic presence. We collect data on attendance at local rural village councils meetings - known as gram panchayat development plan meetings - to analyze impact on citizen participation and government engagement. We find that villages that were brought closer to their neighboring counterparts have higher women participation in their development plan meetings. The engagement is also stronger for government line ministries - a ten-kilometer reduction in distance is correlated with the presence of an additional line-ministry representative at these meetings (see Table 1.18. This difference is especially true for key ministries like agriculture and health & family.

Test for differential change in demographics. As discussed in section 1.4, a key underlying assumption crucial for the validity of the specification is no sorting around the subdistrict borders. We do not have village-level migration data to explicitly test this but as documented by Rosenzweig and Stark (1989), rural-to-rural migration is nearly absent in India and only happens for marriage market reasons. We test for changes in population growth rates to check for impact of proximity on these demographics and find no evidence of sorting around new subdistrict borders as illustrated in Table 1.16.

Test for endogeneity of new subdistrict headquarters. In section 1.4 we discuss the potential endogeneity in the placement of these new subdistrict headquarters. Even though the capitals are likely endogenously chosen, we argued the differential change in the distance to headquarters. To further validate the claim, we use a placebo sample of alternate capitals using other large towns in the subdistricts. These larger towns were possible contenders for the choice of subdistrict HQ but were not chosen. The distance of these alternate HQ to the villages would be correlated to the distance of the actual HQ but exogenous to the change in distance for two neighboring villages. We instrument the distance to the new headquarters using the distance to the placebo subdistricts instead. Our keys results are robust to this IV approach as illustrated in Table 1.17.

Further robustness checks. We test our results using subsamples of villages by dropping villages very close to new headquarters as they might have a negative impact if officials in the original headquarters were reassigned to new headquarters in Appendix Table 1.A.3; dropping very large villages (population size greater than 5000 people) in Appendix Table 1.A.4. We include geographic polynomials and test for spatial serial correlation. No discernible differences in estimates were found.

1.6 Conclusion

The issues of state effectiveness and governance inequality have been significant subjects in policy research discussions. We document substantial spatial inequality in government investment within a local jurisdiction. Using detailed high-resolution village-level data spanning over 55 years and leveraging a natural experiment that quadrupled the number of subdistricts in an Indian state, we demonstrate that bringing the government closer to the people leads to enhanced access to public services and the potential for long-term state capacity improvement. Our findings highlight the crucial role of spatial organization in public administration as a barrier to the equitable provision of public goods. Reducing the distance between citizens and the state can effectively enhance the state's capacity to deliver and monitor public goods in rural areas, thus reducing spatial disparities in living standards.

Why does distance to administration reduce the availability of public goods? There are several possible reasons, from the perspectives of both the state (supplier of public goods) and the citizens (consumers of public goods). We find that a reduction in distance to administration improved civic engagement and bureaucrat attendance at local meetings even 35 years later. Future work would hope to use data from neighboring states to disentangle treatment effects in this paper.

Policies that reduce distance, such as redrawing administrative borders or changing the location of administrative headquarters or creating smaller administrative units, pose additional fiscal costs. Figure 1.3 hints at mechanical catch-up even without the policy reform. The subdistrict split helped speed the process where distance played a key mediating role for remote villages as suggested by our analysis, but it came at a significant cost and reallocation of resources. Understanding the cost-effectiveness is challenging given we only study a subset of outcomes and demand further analysis. Developing countries would have to evaluate whether the additional benefits in terms of expanded rural opportunities and reduced spatial disparities are worth the potential cost.

1.7 Figures and Tables

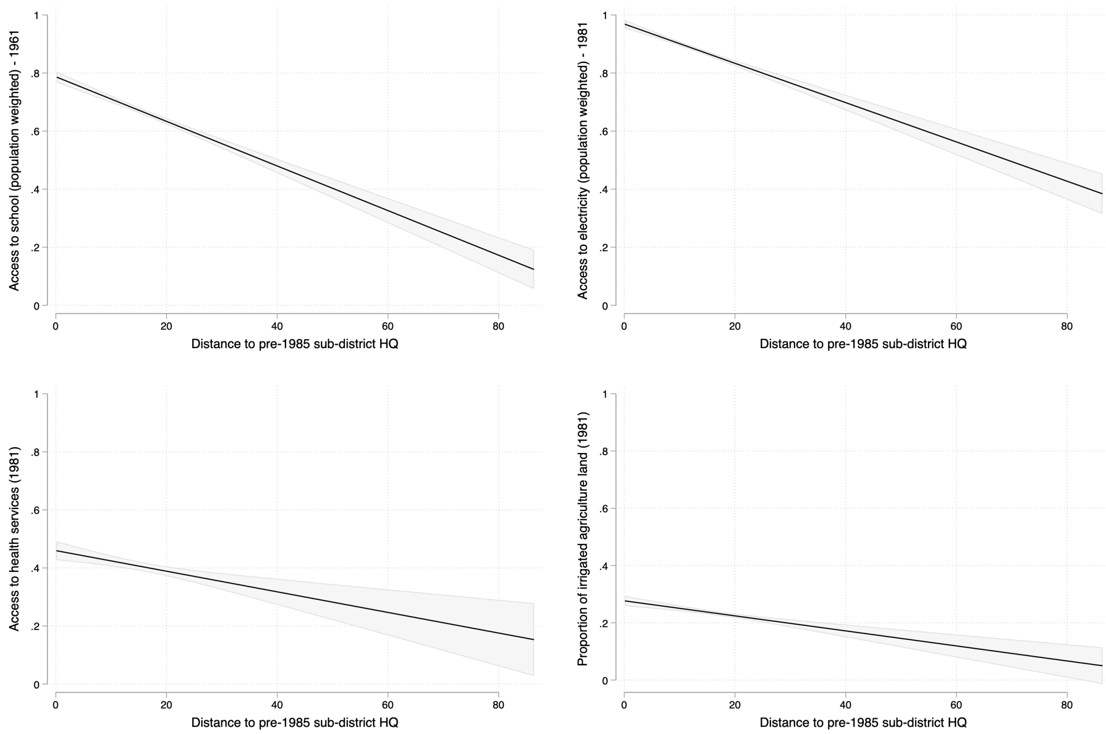


Figure 1.1. Documenting spatial heterogeneity public goods provision (1961)

These graphs plot linear fit of probability of access to a public good in 1961 plotted against the distance to old subdistrict headquarters (in km). Top left presents access to primary school within 5km radius of the village (weighted by the population), top right is access to electricity in the village, bottom left is access to any health services within 5km of the village (including dispensary, health centers, hospitals), and bottom right is the proportion of the total agricultural land that is irrigated.

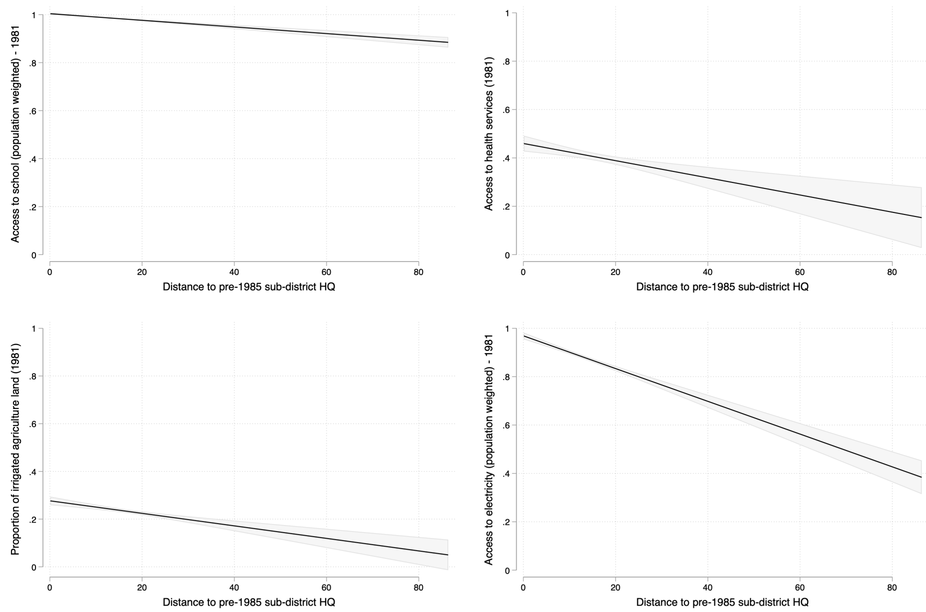


Figure 1.2. Documenting spatial heterogeneity public goods provision (1981)

These graphs plot linear fit of probability of access to a public good in 1961 plotted against the distance to old subdistrict headquarters (in km). Top left presents access to a primary school within 5km radius of the village (weighted by the population), top right is access to any health services within 5km of the village (including dispensary, health centers, hospitals), bottom left is the proportion of the total agricultural land that is irrigated, and bottom right is access to electricity in the village.

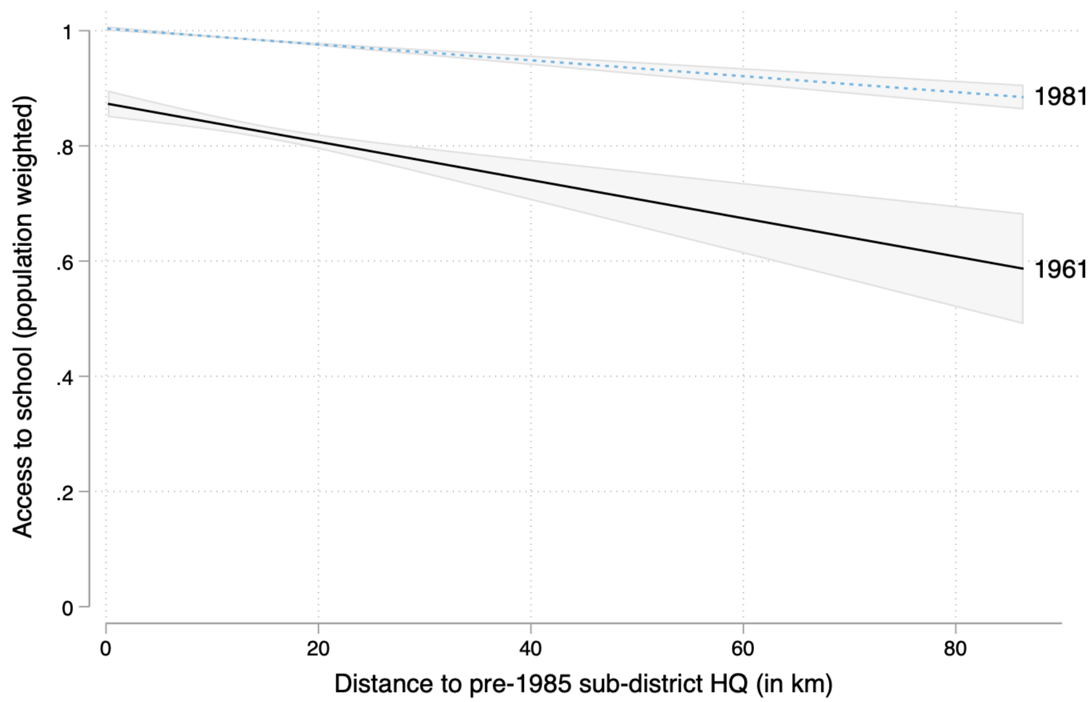


Figure 1.3. Change in access to public schools

This figure plots the linear fit of probability of access to a school within 5km of a village against the distance to old subdistrict headquarters. The black solid line reflects data in 1961 and the blue dotted line is for 1981.

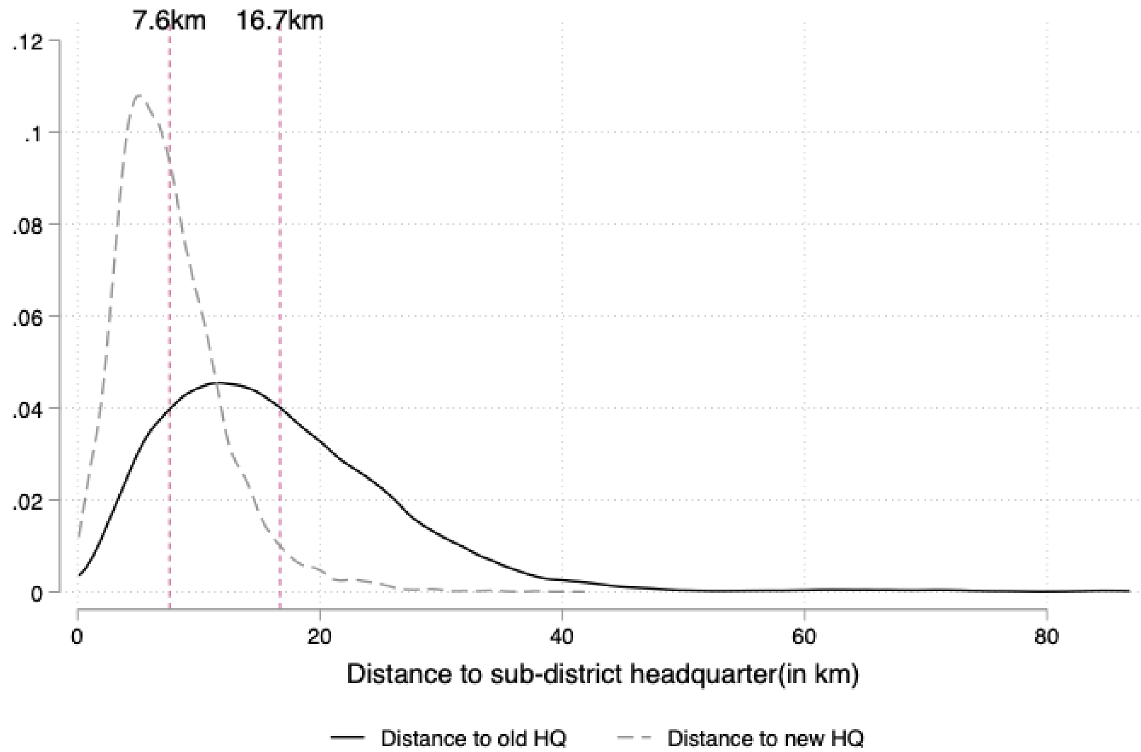


Figure 1.4. Reduction in distance to headquarters

The density plot shows the distribution of the original distance to headquarters (before split) in black solid line and the distribution of the distance to new subdistrict headquarters post-split in black dashed line. The average distance pre-split was 16.7km, which was reduced to an average distance of 7.6km post-split.

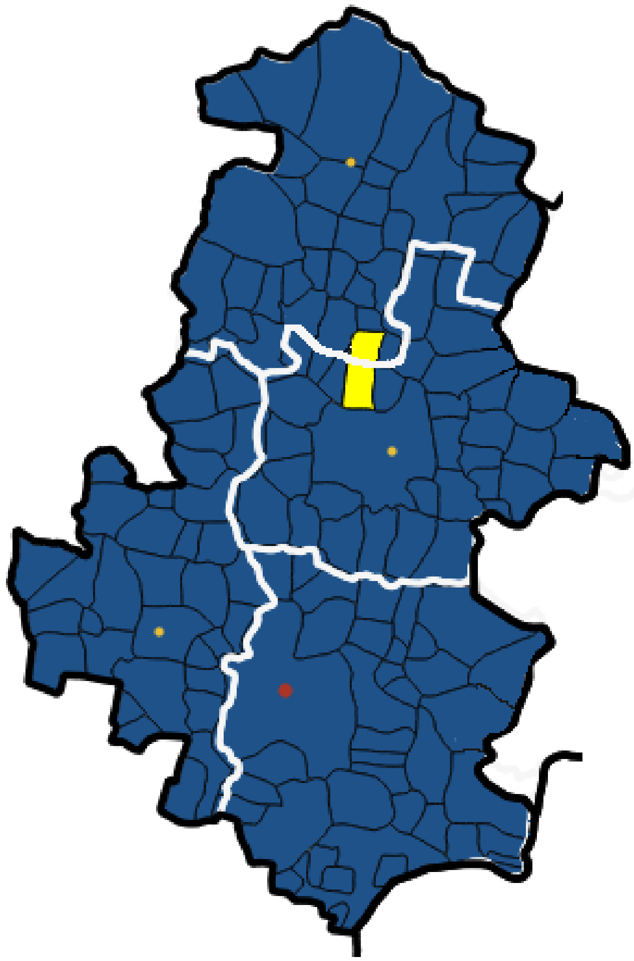


Figure 1.5. Illustration of empirical strategy

Example of our empirical strategy, showing one subdistrict prior to policy change (black boundary). The subdistrict was subdivided into four subdistricts in 1985 marked by white boundaries. Each small blue polygon is a village in the study sample. The orange and yellow dots represent the orginal and new subdistrict headquarters respectively. We pick two villages (highlighted in yellow) that were originally in the same subdistrict and almost equidistant to the old subdistrict headquarters (orange dot), but post-policy change were placed in different subdistricts and thus have differing distance to their new headquarters.

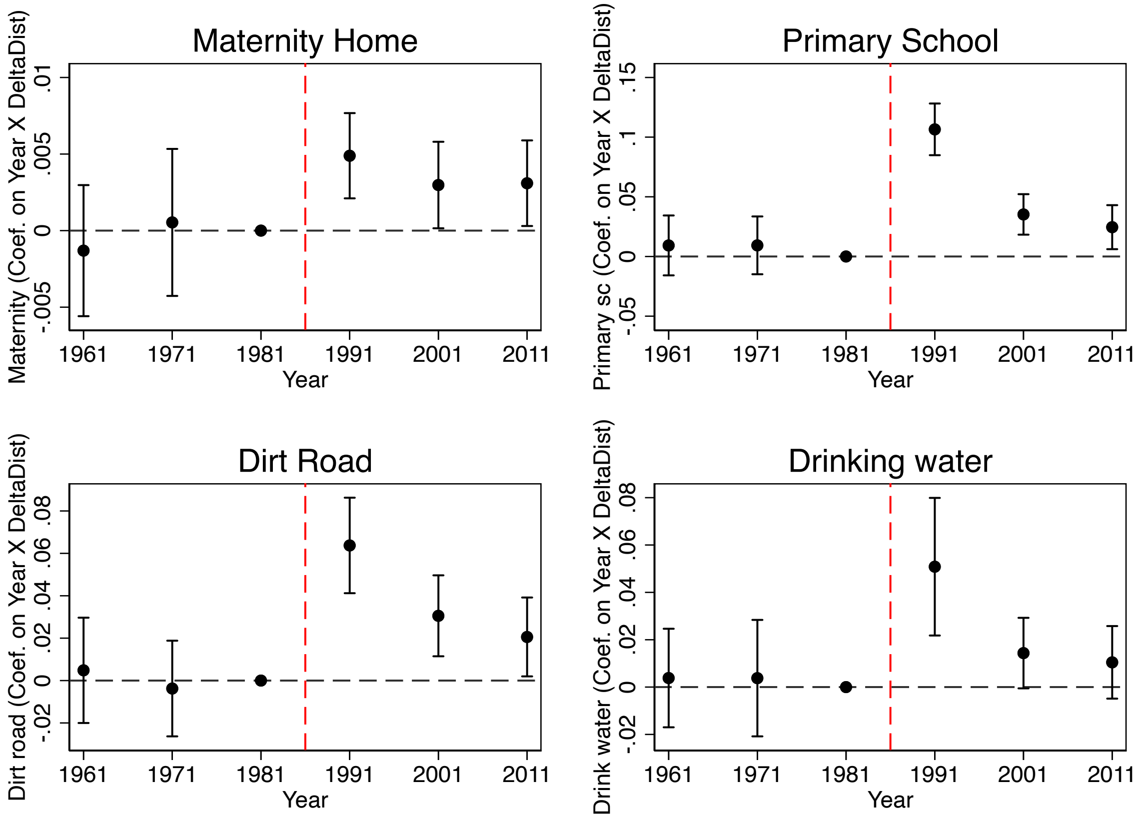


Figure 1.6. Event study

These graphs report coefficient estimates and 95% confidence intervals from event study versions of the regressions. The red dashed line presents the policy event in 1985. The reference period 1981 is the 4 years just prior to the split. The outcome variable for top left is the access to a maternity home within 5km of the village, top right is the access to primary schools within 5km of the village, bottom left is access of village to a dirt road, and bottom right is access to drinking water in the village.

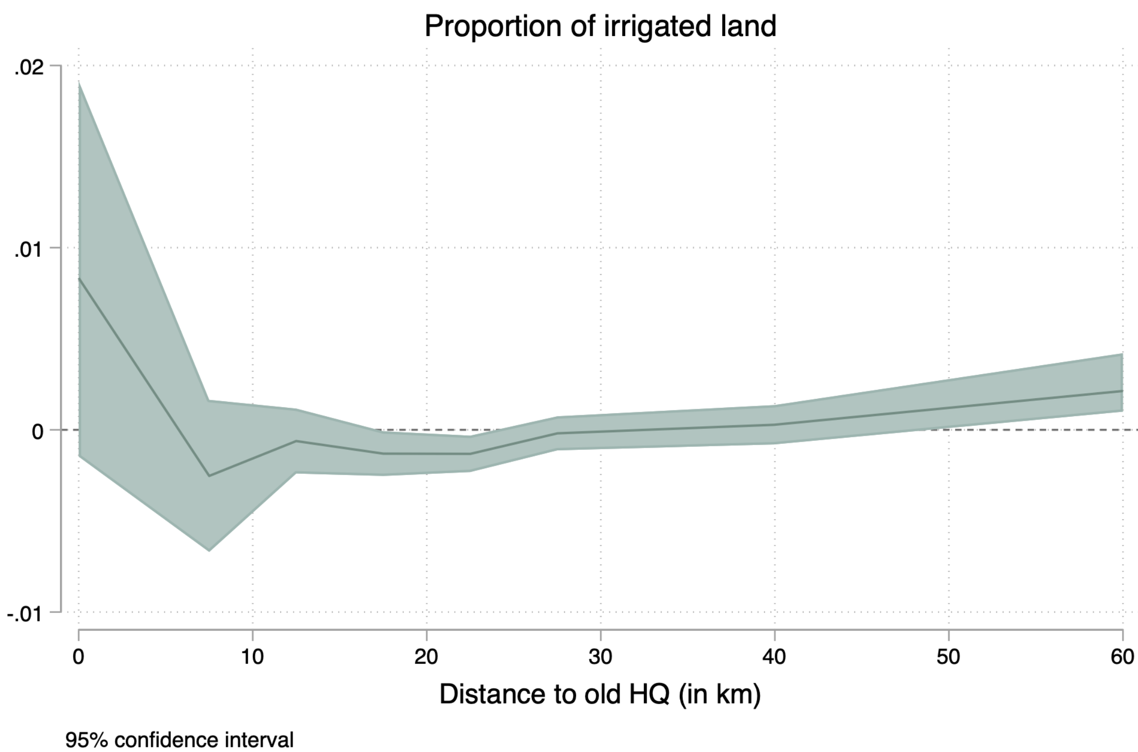


Figure 1.7. Potential catch-up for Remote villages - irrigation access in 1991

These graphs plot the coefficient estimates and 95% confidence intervals of access to irrigation on change in distance non-parametrically as a function of the distance of the village to the old HQ.

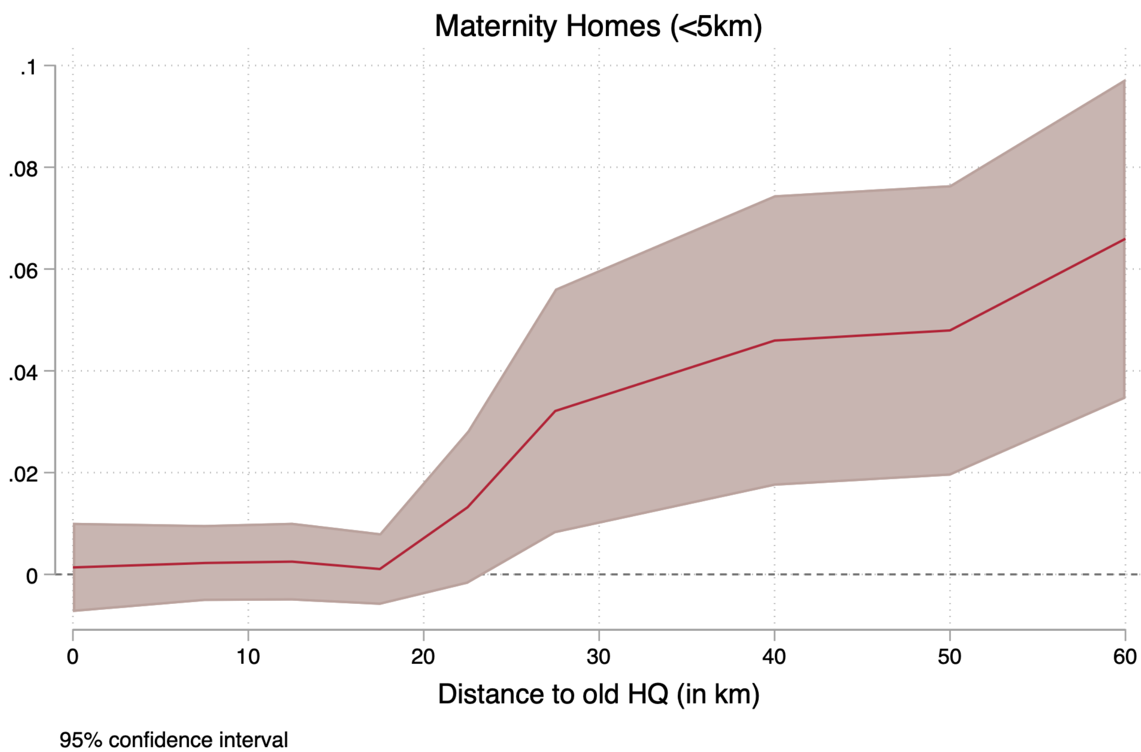


Figure 1.8. Access to maternity center in 1991

These graphs plot the coefficient estimates and 95% confidence intervals of access to a maternity home on change in distance non-parametrically as a function of the distance of the village to the old HQ.

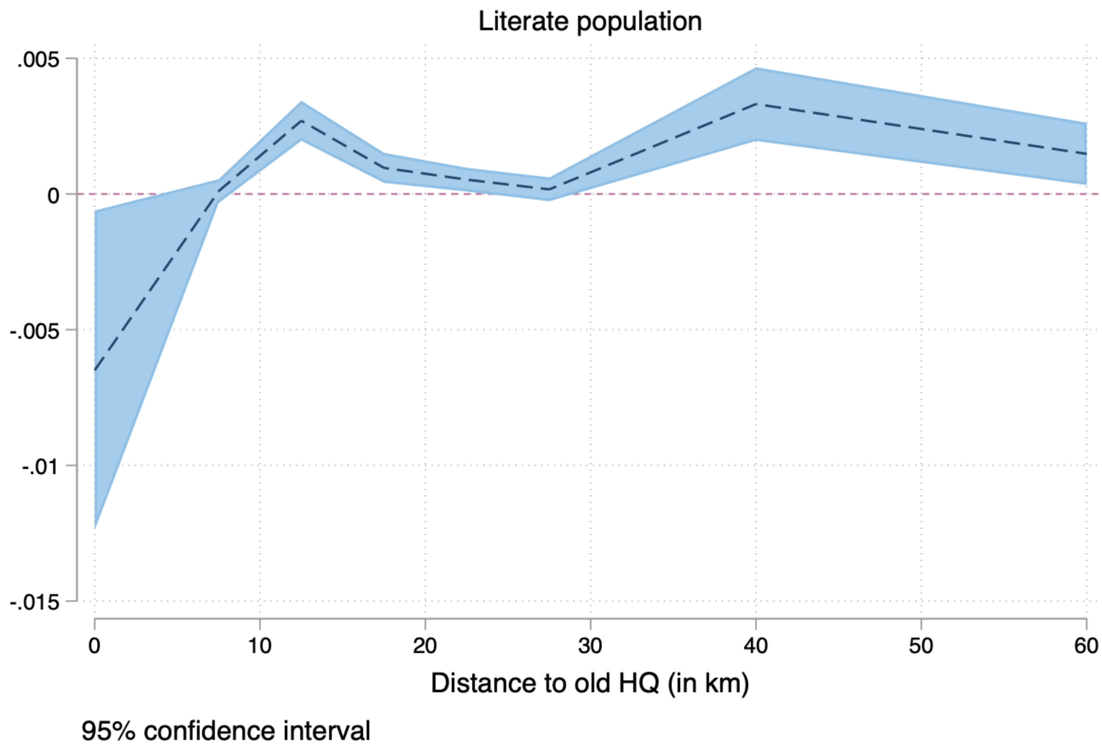


Figure 1.9. Long run (2011) impact on literacy by distance to old HQ

These graphs plot the coefficient estimates and 95% confidence intervals of village literacy rate on change in distance non-parametrically as a function of the distance of the village to the old HQ.

Table 1.1. Descriptive statistics - pre-reform (1981)

	# Villages	Mean	Std. Dev.
Demographic variables			
1981 Population	9776	1486.1	1655.2
Prop. of SC/ST population	9476	0.36	0.31
Prop. of literate population	9475	0.23	0.11
Prop. of ag workers (male)	9776	0.81	0.14
Distance to Sub-district HQ (km)	9776	16.7	10.3
Public goods			
Prop. of villages with primary schools (<5km)	9776	0.89	0.31
Prop. of villages with a maternity home (< 5km)	9776	0.01	0.42
Prop. of villages with dirt road	9776	0.48	0.46
Prop. of villages with drinking water	9776	0.97	0.17

Notes: The table presents descriptive statistics of demographic variables and access to public amenities for villages in our study sample.

Table 1.2. Balance Tests: Correlation of change in Distance with pre-reform demographics

	(1) Population 1981	(2) Prop. SC-ST 1981	(3) Prop in agr 1981	(4) Literate population	(5) Altitude
△ Dis to HQ	116.00	0.121	0.003	0.000	0.115
	(119.76)	(0.112)	(0.003)	(0.002)	(0.703)
# Villages	5868	5814	5870	5410	5830
Village pair FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair design estimates of demographic and geographical variables on change in distance to subdistrict HQ. Column 1 presents pre-split 1981 population levels, column 2 presents the proportion of scheduled caste and scheduled tribes in 1981 which is the proportion of marginalized communities, column 3 presents the proportion of agriculture share of employment in the village in 1981, column 4 presents the share of literate population in 1981, and column 5 presents effect on altitude. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.3. Balance Tests: Correlation of Change in Distance with pre-reform public good provision

	(1) Access to Primary School (<5km)	(2) Acces to Dirt Road	(3) Access to Maternity Homes (<5km)	(4) Drinking Water	(5) Prop. of Agr land with irrigation access
△ Dis to HQ	-0.013	0.023	0.011	0.009	0.020
	(0.019)	(0.021)	(0.008)	(0.011)	(0.019)
# Villages	5868	5814	5868	5870	5410
Village pair FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair design estimates of access to public goods in 1981 on change in distance to subdistrict HQ. Columns 1-5 present the impact on access to primary school, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.4. Parallel Trends: Correlation of Change in Distance with changes in pre-reform public good provision (1981-1961)

	(1) **ΔAccess to Primary School (<5km)**	(2) **ΔAccess to Dirt Road**	(3) **ΔAccess to Maternity Homes (<5km)**	(4) **ΔDrinking Water**	(5) **ΔProp. of Agr land with irrigation access**
△ Dis to HQ	-0.002	0.001	0.003	0.001	0.000
	(0.003)	(0.001)	(0.002)	(0.004)	(0.001)
# Villages	5868	5814	5868	5870	5410
Village pair FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair design estimates of change in access to public goods between 1961 and 1981 on change in distance to subdistrict HQ. Columns 1-5 present the impact on access to primary school, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.5. Match-Pair: Impact on public good provision by 1991

	(1) **Access to Primary School (<5km)**	(2) **Access to Post Office**	(3) **Access to Maternity Home (<5km)**	(4) **Drinking Water**	(5) **Access to Dirt Road**	(6) **Prop. of Agr land with irrigation access**
△ Dis to HQ	0.871***	0.668***	0.064**	0.352***	0.218***	0.807***
	(0.201)	(0.104)	(0.038)	(0.121)	(0.102)	(0.300)
DV Mean (81-61)	0.13	0.07	0.02	0.32	0.08	0.19
# Villages	5868	5814	5868	5870	5410	5830
Village pair FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair design estimates of access to public goods in 1991 on change in distance to subdistrict HQ. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.6. Long differences: Impact on public good provision by 1991

	(1) **Access to Primary School (<5km)**	(2) **Access to Post Office**	(3) **Access to Maternity Home (<5km)**	(4) **Drinking Water**	(5) **Access to Dirt Road**	(6) **Prop. of Agr land with irrigation access**
△ Dis to HQ	0.798***	0.667***	0.076**	0.333***	0.209**	0.823***
	(0.221)	(0.121)	(0.039)	(0.148)	(0.118)	(0.299)
# Villages	8867	8755	8815	8138	8211	8830
Clusters	2331	2271	2338	2171	2293	2332

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the long-difference (pooling all villages) estimates of access to public goods in 1991 on change in distance to subdistrict HQ. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary segment level as discussed in section 1.4.

Table 1.7. Potential catch-up for Remote villages (1991)

	(1) Access to Primary School (<5km)	(2) Access to Post Office	(3) Access to Maternity Home (<5km)	(4) Drinking Water	(5) Access to Dirt Road	(6) Prop. of Agr land with irrigation access
△ Dis to HQ	0.000	0.030***	0.001	0.027***	0.000	0.002
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
1[Disold>25] **x** △ Dis	0.902***	0.625***	0.083***	0.367*	0.252***	0.802***
	(0.005)	(0.007)	(0.002)	(0.205)	(0.011)	(0.001)
# Villages	8867	8755	8815	8138	8211	8830
Subdistrict FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the long-difference (pooling all villages) estimates of access to public goods in 1991 on change in distance to subdistrict HQ. **1**[Disold>25] refers to villages with distance to old subdistrict HQ further than 25km. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary segment level as discussed in section 1.4.

Table 1.8. Match pair: Impact on state/district provided public goods (1991 outcomes)

	(1) **Electricity**	(2) **Tarr Road**	(3) **Hospital**	(4) **Middle/High School**	(5) **Canal**
△ Dis to HQ	0.488	0.028	0.021	0.062	0.008
	(0.662)	(0.071)	(0.069)	(0.066)	(0.022)
DV Mean (91-81)	0.29	0.05	0.14	0.09	0.21
# Villages	5860	5868	5870	5868	5842
Village pair FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair estimates of access to public goods in 1991 on change in distance to subdistrict HQ. Columns 1-5 present the impact on access to electricity, tarr road, hospital, high school, irrigation canal, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.9. Match pair: Long-run impact on public good provision in 2011

	(1) Access to Primary School (<5km)	(2) Access to Post Office	(3) Access to Maternity Home (<5km)	(4) Drinking Water	(5) Access to Dirt Road	(6) Prop. of Agr land with irrigation access
△ Dis to HQ	0.719	0.533	0.029	0.225	0.028	0.013
	(0.605)	(0.527)	(0.053)	(0.743)	(0.062)	(0.011)
# Villages	5630	5612	5630	5668	5402	5624
Village pair FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair estimates of access to public goods in 2011 on change in distance to subdistrict HQ. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.10. Long difference: Impact on public good provision in 2011

	(1) Access to Primary School (<5km)	(2) Access to Post Office	(3) Access to Maternity Home (<5km)	(4) Drinking Water	(5) Access to Dirt Road	(6) Prop. of Agr land with irrigation access
△ Dis to HQ	0.000	0.000	0.000	0.011***	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.001)
# Villages	9653	9179	9179	9041	9441	9534
Clusters	2631	2471	2471	2371	2592	2618

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the long-difference (pooling all villages) estimates of access to public goods in 2011 on change in distance to subdistrict HQ. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary segment level as discussed in section 1.4.

Table 1.11. Long difference: Impact on Literacy and Occupation in the short run (1991 outcomes)

	(1) Literate population	(2) Prop of Agr workers	(3) Prop of Ind workers	(4) Prop of Agr workers (male)
△ Dis to HQ	0.010**	-0.001	0.000	-0.001
	(0.008)	(0.000)	(0.000)	(0.000)
# Villages	5868	5814	5866	5870
Village pair FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table presents the match-pair estimates of economic outcomes in 1991 on change in distance to subdistrict HQ. Columns 1-4 present the literacy rate, agricultural share of employment, manufacturing share of employment, and agricultural share of male employment, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary segment level as discussed in section 1.4.

Table 1.12. Long difference: Long run (2011) occupation and literacy impacts

	(1) Literate population	(2) Nightlights	(3) Prop of Agr workers	(4) Prop of Ind workers	(5) Prop of Agr workers (male)
△ Dis to HQ	0.011*	0.383***	-0.001	0.012**	-0.018***
	(0.001)	(0.100)	(0.001)	(0.008)	(0.001)
# Villages	5630	5612	5630	5668	5402
Village pair FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table presents the long-difference pooled estimates of economic outcomes in 2011 on change in distance to subdistrict HQ. Columns 1-5 present the literacy rate, average nightlights, agricultural share of employment, manufacturing share of employment, and agricultural share of male employment, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary segment level as discussed in section 1.4.

Table 1.13. Match pairs: Long-run impact on state capacity (NREGS 2015)

	(1) Total	(2) STs	(3) SCs	(4) Non-SCs/STs
Panel A: Log Jobcards				
△ Dis to HQ	0.052**	0.011	0.132***	0.097
	(0.025)	(0.062)	(0.046)	(0.078)
Panel B: Workdays				
△ Dis to HQ	0.043	0.095	0.224***	0.056
	(0.047)	(0.114)	(0.087)	(0.083)
Panel C: Log Amount Disbursed (to PO account)				
△ Dis to HQ	0.098***			
	(0.032)			
# Villages	5860	5860	5860	5860
Village Pair FE	Yes	Yes	Yes	Yes

Notes: The table presents the match-pair estimates of NREGA outcomes in 2015 on change in distance to subdistrict HQ. Column 1 presents the total, 2-4 by subgroups of marginalised and non-marginalised communities. Panel A refers to total log jobcards issued in the village, panel B presents total number of workdays, and Panel C presents total disbursement of funds. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.14. Long difference: Long-run impact on state capacity (NREGS 2015)

	(1) Total	(2) STs	(3) SCs	(4) Non-SCs/STs
Panel A: Log Jobcards				
△ Dis to HQ	0.045**	0.021	0.133***	0.109*
	(0.023)	(0.065)	(0.042)	(0.075)
Panel B: Log Households worked				
△ Dis to HQ	0.042	0.001	0.142***	0.078
	(0.031)	(0.063)	(0.052)	(0.066)
Panel C: Workdays				
△ Dis to HQ	0.038	0.091	0.228***	0.053
	(0.043)	(0.117)	(0.082)	(0.084)
# Villages	7497	7497	7497	7497
Clusters	1882	1882	1882	1882

Notes: The table presents the long-difference (pooled) estimates of NREGA outcomes in 2015 on change in distance to subdistrict HQ. Column 1 presents the total, 2-4 by subgroups of marginalised and non-marginalised communities. Panel A refers to total log jobcards issued in the village, Panel B presents total number of households that worked in NREGS, and Panel C presents total number of workdays. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary level as discussed in section 1.4.

Table 1.15. Long difference: Long-run impact on state capacity (NREGS 2015)

	(1) **Assets Approved**	(2) **log(Estimated Amount)**	(3) **log(Actual Expenditure)**	(4) **log(Amt disbursed to PO account)**
△ Dis to HQ	1.107	0.022	0.084	0.088*
	(1.156)	(0.058)	(0.103)	(0.052)
# Villages	8648	7438	7409	6309
Clusters	2234	1976	1969	1782

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the long-difference (pooled) estimates of NREGA outcomes in 2015 on change in distance to subdistrict HQ. Column 1 presents the total assets approved, column 2 presents log of the estimated amount budgeted, column 3 is total log expenditure reported, and panel 4 presents actual amount disbursed into workers post office accounts. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary level as discussed in section 1.4.

Table 1.16. Changes in demographics in 2011

	(1) Population 2011	(2) Proportion SC-ST 2011	(3) # Households 2011	(4) Pop growth (1981-2011)
△ Dis to HQ	11.508	-0.001	1.076	0.012
	(9.141)	(0.001)	(1.747)	(0.015)
# Villages	9972	9713	9746	9544
R-squared	0.426	0.607	0.468	0.250
Subdistrict FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the long-difference (pooled) estimates of demographic outcomes in 2011 on change in distance to subdistrict HQ. Column 1 presents the total population in 2011, column 2 presents proportion of marginalised SC-ST communities in 2011, column 3 presents total number of households in 2011, and column 4 presents population growth between 1981 and 2011. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary level as discussed in section 1.4.

Table 1.17. Match Pairs: Impact on public good provision by 1991 (using distance to placebo HQ as IV)

	(1) Access to Primary School (<5km)	(2) Access to Post Office	(3) Access to Maternity Home (<5km)	(4) Drinking Water	(5) Access to Dirt Road	(6) Prop. of Agr land with irrigation access
△ Dis to HQ	0.696***	0.558***	0.063***	0.328***	0.134**	0.785***
	(0.233)	(0.130)	(0.031)	(0.119)	(0.068)	(0.267)
# Villages	5868	5814	5868	5870	5410	5830
Village pair FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair design estimates of access to public goods in 1991 on change in distance to subdistrict HQ. Here we use change in distance to alternatively constructed placebo HQ as IV. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.18. Civic engagement and bureaucrat attendance

	Civic engagement			Bureaucrat presence		
	(1) GS meeting attendance Prop of women	(2) GS meeting attendance Prop of SC-ST	(3) Elected Representatives	(4) Bureaucrat attendance	(5) Bureaucrat attendance agriculture	(6) Bureaucrat attendance health and family
△ Dis to HQ	0.009*	0.000	0.565*	0.081*	0.025*	0.023*
	(0.005)	(0.000)	(0.315)	(0.046)	(0.015)	(0.013)
Mean	0.28	0.46	10.0	5.1	0.43	0.35
# Villages	3524	3522	4928	3524	3524	3524
Clusters	369	369	424	369	369	369

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the long-difference specification results of public attendance in local Gram Panchayat meetings (columns 1 and 2), total number of representatives elected in column 3, and attendance of frontline workers in Gram Panchayat meetings (columns 4-6). Standard errors were clustered at the subdistrict-boundary level as discussed in section 1.4.

1.8 Additional Figures and Tables

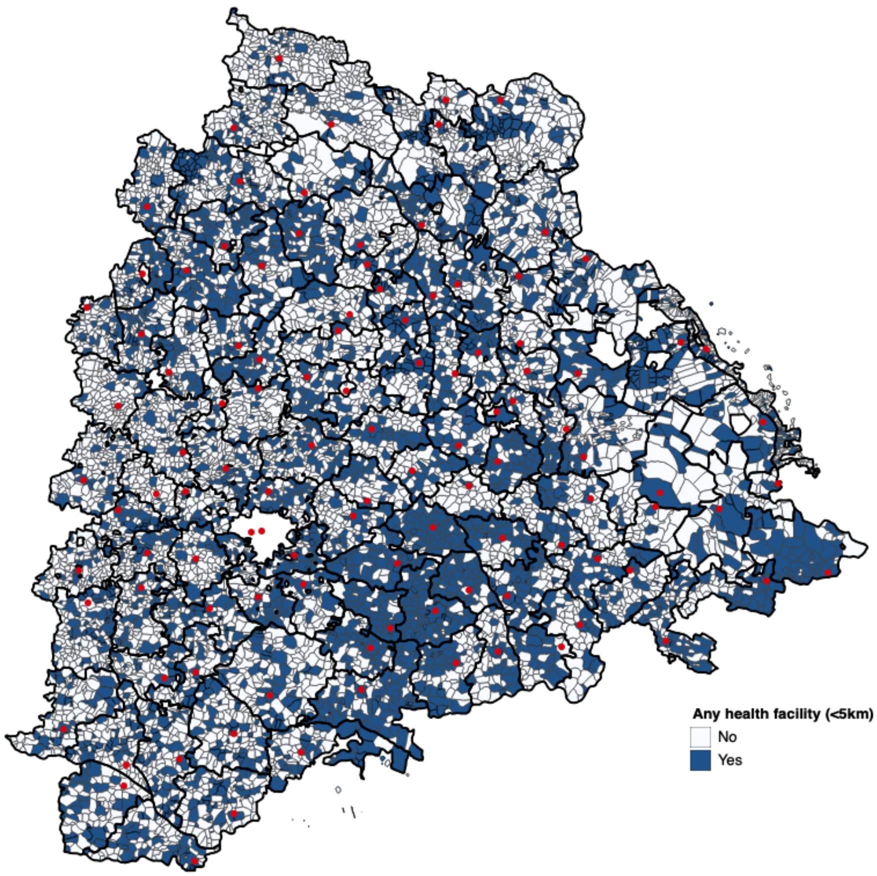


Figure 1.A.1. Spatial inequality in public good provision (1981)

This figure provides an example of geographic inequality in the provision of public good. Here we plot access to any health facility within 5km of a village. The red dots are the old subdistrict headquarters. Black lines refer to old subdistrict boundaries. Villages with access to any healthcare facility in 1981 is shown in blue.

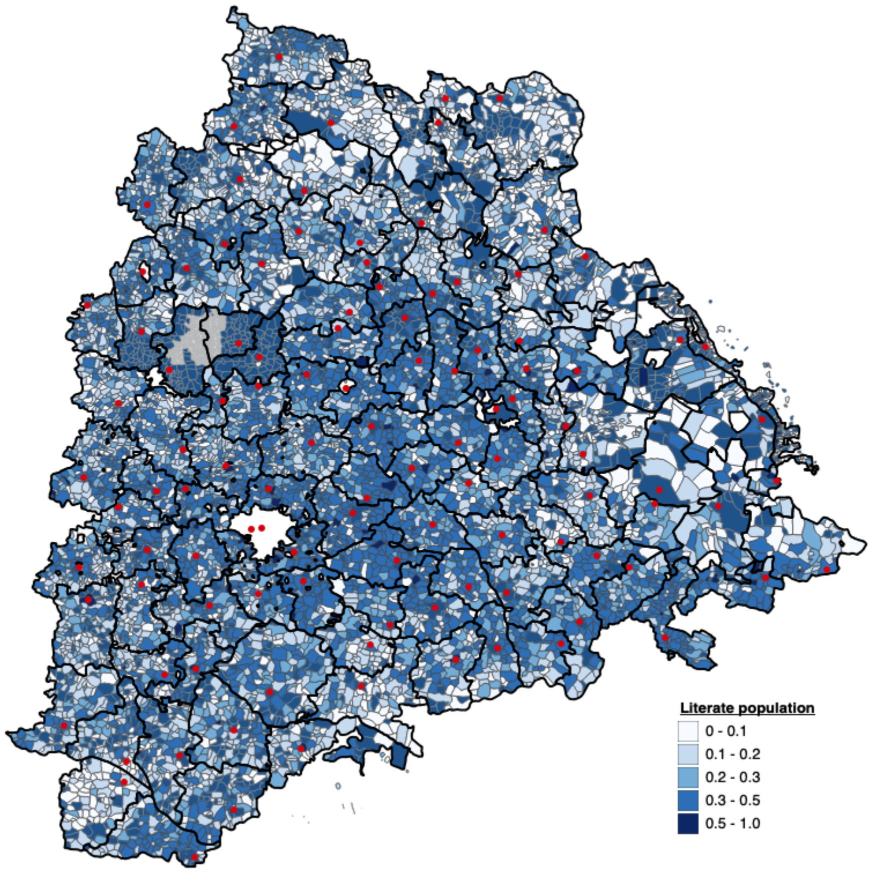


Figure 1.A.2. Spatial inequality - literate population

This figure provides an example of geographic inequality in economic outcomes (here, we plot literacy rate). Here we plot access to any health facility within 5km of a village. The red dots are the old subdistrict headquarters. Black lines refer to old subdistrict boundaries. Villages with a larger share of literate population in 1981 are shown in a darker blue color.

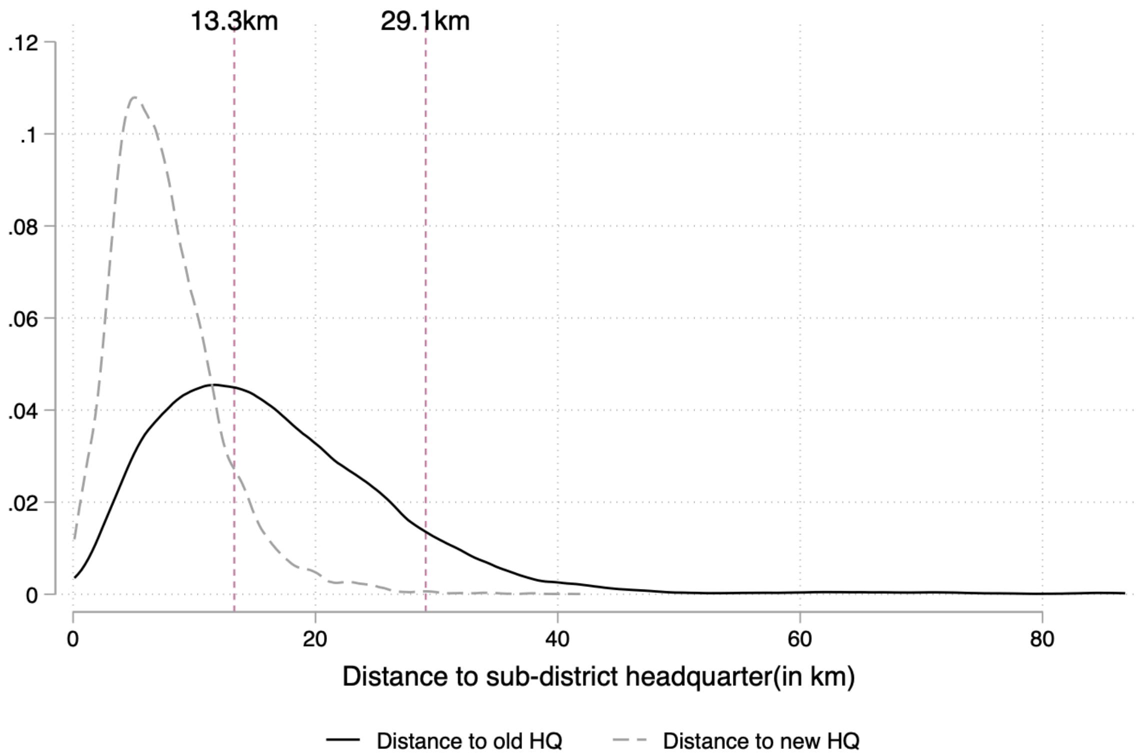


Figure 1.A.3. Reduction in distance to headquarters: 90th percentile

The density plot shows the distribution of the original distance to headquarters (before split) in black solid line and the distribution of the distance to new subdistrict headquarters post-split in black dashed line. The 90th percentile in distance distribution pre-split was 29.1 km, which was reduced to 13.3km post-split.

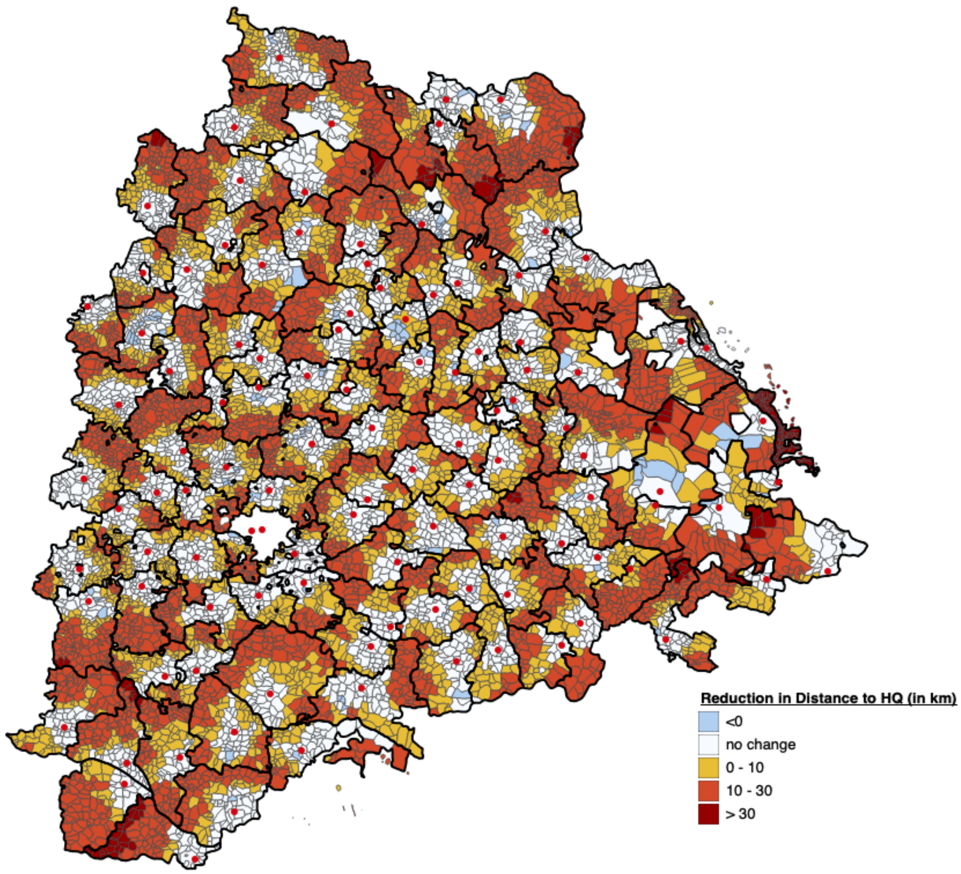


Figure 1.A.4. Reduction in distance to headquarters

This figure is the spatial version of Figure 1.4 plotting the reduction in distance of a village to its local government subdistrict headquarter. he red dots are the old subdistrict headquarters. Black lines refer to old subdistrict boundaries. Villages with larger reduction in distance to their subdistrict headquarters are shown in a darker color.

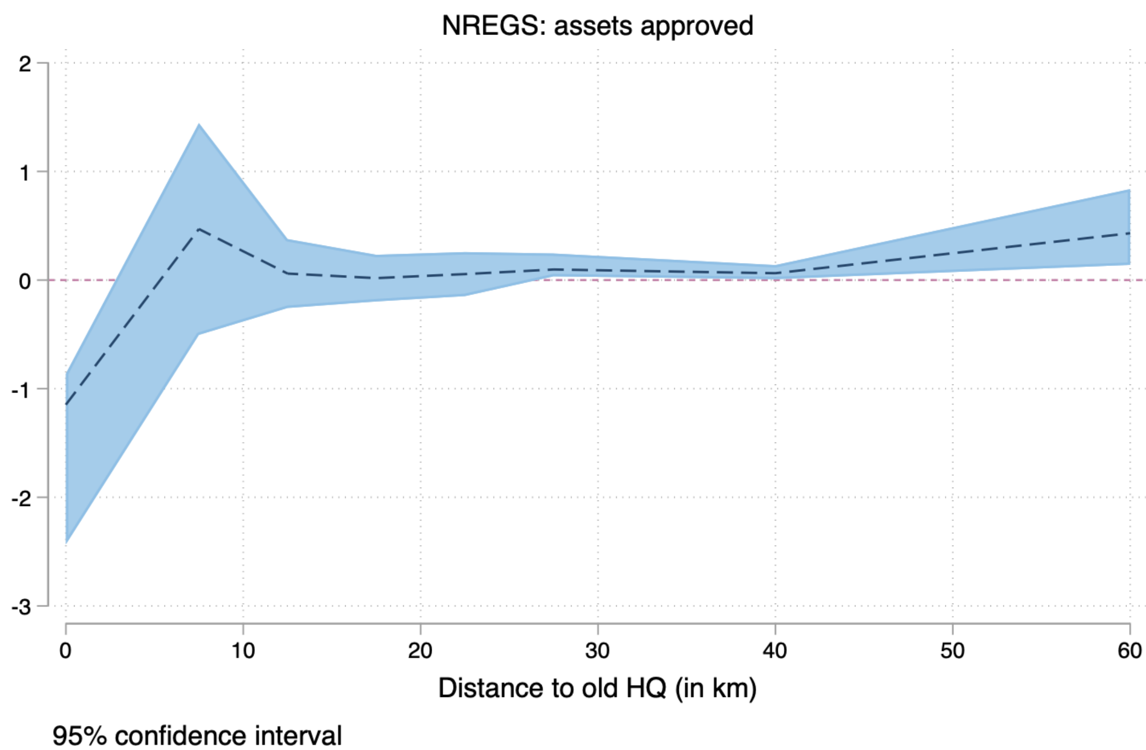


Figure 1.A.5. NREGS implementation impact by distance to old HQ (assets)

These graphs plot the coefficient estimates and 95% confidence intervals of assets approved under NREGA on change in distance non-parametrically as a function of the distance of the village to the old HQ.

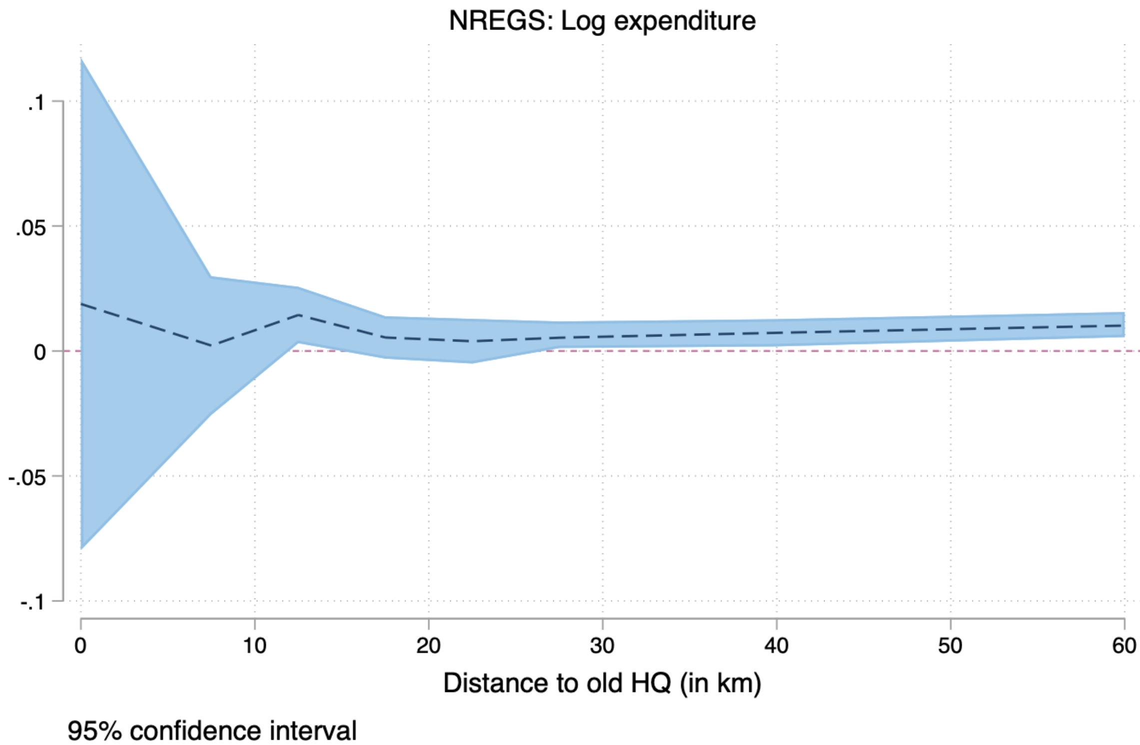


Figure 1.A.6. NREGS implementation impact by distance to old HQ (expenditure)

These graphs plot the coefficient estimates and 95% confidence intervals of expenditure on NREGA on change in distance non-parametrically as a function of the distance of the village to the old HQ.

Table 1.A.1. Long difference: Impact on public good provision in 2021

	(1) **Brick road**	(2) **All-weather road**	(3) **Hrs of electricity**	(4) **Piped tap water**
△ Dis to HQ	0.018***	0.000	0.000	0.001
	(0.006)	(0.000)	(0.000)	(0.006)
Mean	0.84	0.87	0.87	0.81
# Villages	4928	4928	4928	4928
Clusters	424	424	424	424

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the long-difference (pooling all villages) estimates of access to public goods in 2020 on change in distance to subdistrict HQ. The key outcome variables come from the Mission Antyodaya dataset. Columns 1-4 present the impact on access to a brick road, access to an all-weather tarr road, probability of 24 hours of electricity (in a day), access to piped drinking water, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the subdistrict-boundary segment level as discussed in section 1.4.

Table 1.A.2. Effects on rural consumption, employment, and poverty

	(1) **Share of agr households**	(2) **Consumption pc**	(3) **Poverty rate**
△ Dis to HQ	0.010	70.055	0.002
	(0.012)	(141.077)	(0.003)
# Villages	5630	5624	5630
Village pair FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair estimates of economic outcomes in 2011 on change in distance to subdistrict HQ. Columns 1 presents the share of households in agriculture, column 2 presents avergae consumption per capita in a village, and column 3 presents imputed poverty rate, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.A.3. Impact on public good provision by 1991: removing villages close to the new headquarters

	(1) Access to Primary School (<5km)	(2) Access to Post Office	(3) Access to Maternity Home (<5km)	(4) Drinking Water	(5) Access to Dirt Road	(6) Prop. of Agr land with irrigation access
△ Dis to HQ	0.699***	0.582***	0.059**	0.367***	0.201***	0.778***
	(0.329)	(0.289)	(0.034)	(0.118)	(0.101)	(0.315)
# Villages	5668	5612	5668	5668	5210	5628
Village pair FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the match-pair design estimates of access to public goods in 1991 on change in distance to subdistrict HQ. Here we drop villages within 5km of the new subdistrict headquarters. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Table 1.A.4. Impact on public good provision by 1991: dropping large villages

	(1) Access to Primary School (<5km)	(2) Access to Post Office	(3) Access to Maternity Home (<5km)	(4) Drinking Water	(5) Access to Dirt Road	(6) Prop. of Agr land with irrigation access
△ Dis to HQ	0.681***	0.577***	0.059**	0.355***	0.198***	0.776***
	(0.311)	(0.288)	(0.033)	(0.112)	(0.088)	(0.306)
# Villages	5280	5214	5264	5264	5012	5230
Village pair FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Notes: The table presents the match-pair design estimates of access to public goods in 1991 on change in distance to subdistrict HQ. Here we drop villages with population greater than 5000 people in 1981. Columns 1-6 present the impact on access to primary school, access to a post office in the village, access to dirt road, access to maternity homes, access to drinking water, and the proportion of agricultural land that is irrigated, respectively. Change in distance is the reduction in distance measured in kilometers multiplied by 10. Standard errors were clustered at the village-pair level as discussed in section 1.4.

Chapter 2

Turning Points in Tax Collection

2.1 Introduction

Accelerating the process of achieving a high level of tax collection and preventing its erosion is an important policy issue in countries worldwide. Research in economics has approached the question of the determinants of tax collection from multiple angles, highlighting the importance of economic changes, institutional and administrative structure, and political economy factors. These studies provide theoretical insights into where and why we might expect to see large and sustained changes in countries' tax performance. But how often do we actually see such turning points in the data? Over the past 5 decades, when and where have turning points been most prevalent? Do countries differ in their exposure to sustained downturns in tax collection versus upturns? And what factors are associated with the onset of these turning points?

In this paper, we make some progress on addressing these questions by developing a method to detect turning points in tax collection and (descriptively) investigating their determinants. Our methodology is based on the methods developed in the economic growth literature, which seeks to estimate the presence of break points in countries' GDP growth rates (Kar et al., 2013; Berg, Ostry, and Zettelmeyer, 2012). We implement a variant of this method that statistically detects (potentially multiple) breaks in the growth of a country's tax/GDP ratio. We impose an 8-year period between any two successive break points. In turn, we apply a series of 'filters' to focus on the most economically meaningful growth episodes. Most importantly, in our benchmark setting, we define turning points in tax performance as statistically detected break points that are followed by a period of at least 1 percent absolute growth per year on average in tax/GDP. Turning points are classified as *accelerations* if the average growth rate in tax/GDP is larger in the post-break period than in the pre-break period; conversely, *decelerations* are the turning points where the average growth rate is smaller post-break than pre-break. As detailed in Section 2.3, our selection of parameter values is conservative. We discuss in detail why our method is likely to capture large and sustained turning points, rather than shorter-run volatility in GDP and/or tax/GDP.

Our data comes from the publicly available data-set on tax revenues used in Bachas et al. (2022).[1] For the purposes of this paper, the data-set has two advantageous features. First, it is the most comprehensive data-set on tax revenues, covering the 150 most populous countries from 1965 to 2018, with exceptions only for pre-independence, civil war, and command economy areas. The long time-series within country improves the statistical power of our methodology; the comprehensive coverage across countries allows us to draw broad conclusions about trends in tax performance. Second, the database captures all major taxes, including personal income taxes, corporate income taxes, Social Security payroll taxes, as well as consumption and other indirect taxes.

Applying our method to this data-set yields a set of new findings on turning points in tax performance over the past 50+ years around the world. Our first set of results is about the prevalence and magnitude of turning points. Our method detects a total of 238 turning points. Interestingly, these events are almost evenly spread between accelerations (116 events) and decelerations (122) – if anything, a country picked at a random point in time in the global sample is slightly more likely to experience a sustained downturn rather than a sustained upturn in tax collection.

[1] The database is publicly available online at https://globaltaxation.world

Converting these events to likelihoods, we find that the average likelihood of an acceleration starting in a given year is 3.27% in low and lower-middle income countries (LMICs); 2.72% in upper-middle income countries (UMICs); and, 2.24% in high-income countries (HICs). For decelerations, the numbers are 3.50% in LMICs; 3.30% in UMICs; and, 1.97% in HICs. For both types of turning points, there seems therefore to be a negative development-gradient in the likelihood of occurrence. Somewhat broadly across development groups, both accelerations and decelerations appear less likely in more recent times (2000-2018) than in the earliest decades (1960-1980). Certain regions stand out as having particularly high likelihoods of turning points on average, in particular Sub-Saharan Africa and South Asia.

Apart from the sheer number of break points, the changes in tax/GDP growth post-break are significant in magnitude. Conditional on an acceleration, the average turning point in LMICs features a 12.5% growth rate in tax/GDP post-break. The magnitude of the post-break growth decreases across development, with 11% post-break growth rates in UMICs and 5.7% in HICs. Post-acceleration growth rates are highest in Central and South America (15.6%) and Sub-Saharan Africa (12.2%). Interestingly, the post-break changes in growth rates are lower for decelerations (in absolute terms); in LMICs, the average post-deceleration growth rate is -3.1%.

Our second set of results focuses on the persistence of turning points, as some turning points may persist for longer than the 8-year period imposed in our method. We define persistent and very persistent accelerations (decelerations) as those upward turning points that are not followed by a deceleration (acceleration) within 10 years and within 15 years. Interestingly, we find that most spells that persist for at least 10 years also persist for 15 years. Moreover, the conversion rate from initial spells to very persistent spells is high. For example, 58% of accelerations in LMICs persist for at least 15 years; 50% persist in UMICs; 45% persist in HICs. Decelerations are also quite persistent: 47%, 56% and 65% persist for at least 15 years in LMICS, UMICs, and HICs respectively.

Our third set of results concerns the predictability of these turning points. At the outset, we emphasize that this exercise is not causal nor does it capture precise mechanisms. Instead, the purpose here is to investigate if there are robust empirical associations within-country between the starting point of breaks and changes in a standard set of economic and political variables. We organize the potential determinants in four groups: changes to the political environment; changes to a country's international economic environment; changes to a country's domestic economic environment; and, tax reforms. The exercise is limited by the availability of variables in as broad a sample as our tax/GDP sample. Notwithstanding these limitations, we uncover some interesting patterns. First, changes towards democracy (in the form of a higher Polity V) are very robustly associated with an increase in the likelihood of an acceleration. Second, tax reforms (the introduction of the VAT) and the end of violence (inter-State or intra-State) are also associated with higher likelihood of observing an acceleration, but the results are less precise. Third, there is limited evidence that changes in economic variables are associated with the onset of turning points - though this may partly be due to imperfect measurement of these changes. Finally, our set of explanatory variables does a much poorer job at predicting decelerations than at predicting accelerations.

The rest of the paper is organized as follows. In Section 2.2, we discuss the related literature. In Section 2.3, we define our methodology and data. In Section 2.4, we present our results on the prevalence of turning points, their persistence, and robustness checks. In Section 2.5, we investigate the predictability of turning points relative to a set of economic and political factors. Section 2.6 concludes.

2.2 Literature Review

Our findings are related to several literatures. Of most immediate relevance is the limited set of empirical papers which study turning points in tax/GDP ratios. Akitoby et al. (2018) use a data-set covering 136 countries between 2000 and 2015; they consider episodes defined as 3-year windows of average increase in tax/GDP by 0.5 percentage points per year. Oppel and Chachu (2022) expand the results in Akitoby et al. (2018), using data on 196 countries between 1985 and 2019. They consider 5-year windows, and define the intensity of tax/GDP episodes on the basis of how large the (absolute value of the) change is in percentage point terms. In turn, they create a cumulative score for each country across all periods.[2] Borrowing terminology from the growth literature, both of these studies use 'filter approaches' – which are (subjectively defined) filter-rules to summarize trends. To the best of our knowledge, Dincecco (2009) is the only study which uses statistical approaches to identify breaking points in tax collection, but the author focuses on historical time-series in European countries between 1650 and 1913. Our contribution is to systematically investigate tax performance using a method which combines the statistical approach and the filter approach. Importantly, we apply this framework to the comprehensive data-set on tax/GDP covering 150 countries since 1965.

Our paper is more generally related to a recent and growing literature at the intersection of public finance and development, which seeks to shed light on the determinants of tax capacity. Some of these papers adopt a macro-economic, long-run approach (including Besley and Persson, 2014; Gordon and Li, 2009; Kleven, Kreiner, and Saez, 2016). They document that tax/GDP increases over the development path: this fact holds both within countries, based on the time-series of currently developed countries over the long-run, and across countries, based on the cross-section of countries today which differ in GDP per capita. In the case of within-country trends, the time-frame studied is often very long-run, spanning over 100 years of data. Our paper studies the same tax/GDP outcome, but analyzes changes over a shorter time-horizon of one to two decades. Another set of

[2]Gaspar, Jaramillo, and Wingender (2016) use a historical unbalanced panel of tax/GDP ratios for 139 countries from 1965 to 2011. They show the distribution of tax/GDP ratios in the full sample, but then go on to focus on whether there are tipping points beyond which tax/GDP matter differentially for long-run growth.

papers in this literature provide rigorous, micro-evidence on specific policies which alleviate constraints on tax capacity and cause an increase in tax collection. Using administrative data and experimental variation, Pomeranz (2011) shows that the existence of information trails deters mis-reporting of taxable activities under a VAT. Naritomi (2019) shows that financial incentives provided to consumers can curb mis-reporting at the final stage of the production chain. Kleven, Knudsen, et al. (2011) study randomized audits in Denmark, and find that evasion at the individual level is strongly related to the the extent of third-party coverage. Best et al. (2015) show that implementing turnover taxes can improve enforcement on small firms and ultimately increase tax revenue collection, even if they create distortions (relative to profit taxes). Bergeron, Tourek, and Weigel (2021) show that increasing enforcement capacity allows local governments to simultaneously levy higher tax rates. It is possible that the administrative, enforcement and statutory tax rate reforms studied in these papers, which are shown to have positive effects on tax collection at the micro-level, may trigger the onset of turning points at the macro-economic level.

Our paper is also related to the literature on the cyclicality of fiscal policy (including Gavin and Perotti, 1997; Kaminsky, Reinhart, and Vegh, 2004; Talvi and Vegh, 2005; Ilzetzki and Vegh, 2008), which examine changes in tax revenues or tax rates over the business cycle. Kaminsky, Reinhart, and Vegh (2004) argue that the tax/GDP ratio is an uninformative indicator for studying the cyclicality of fiscal policy, and they focus on tax rates instead. This is because tax revenues constitute a policy outcome that endogenously responds to the business cycle (via a change in tax base). However, since our interest is in studying significant turning points in fiscal *performance*, as measured by the tax/GDP ratio, rather than studying the cyclicality of fiscal *policy*, it is a more meaningful metric for our analysis. Of course, an important concern is that our estimated turning points coincide with GDP growth cycles. We discuss this in detail in Section 2.3.4. A related macro-empirical literature studies tax buoyancy - namely, the responsiveness of the growth rate in tax revenues to growth rate of GDP. Estimates of buoyancy exist for long time-periods and samples of countries from around the world (including Lagravinese, Liberati, and Sacchi, 2020; Gupta, Jalles, and Liu, 2021; Cornevin, Flores, and Angel, 2023). Conceptually, settings where buoyancy is estimated to be well above one (well below one) in the medium-run could be related to the settings where we detect accelerations (decelerations); empirically, studying the overlap between the timing of our detected turning points and these settings where medium-run buoyancy differs from 1 would be an interesting area for future research.

Finally, our focus on turning points in tax performance is naturally related to the topic of tax reforms. Persson and Tabellini (2002) and Alt, Preston, and Sibieta (2009) provide comprehensive literature reviews of the political forces that shape tax policy reform. Recently, Ilzetski (2018) develops a model which shows that *large* changes in the tax code may be easier to enact than smaller ones and such reforms are more politically feasible when the fiscal needs are more pronounced. The author also reviews recent prominent tax reforms in the United States and other countries. For a review of economic effects of the 1986 reform in the US, see Auerbach and Slemrod (1997).

In terms of methodology, our data-framework draws on the recent developments in the empirical literature on economic growth. Pritchett (2000) noted that economic growth is often characterized by frequent 'regime-shifts', which motivated a subsequent literature which focuses on developing techniques to identify the timing of breaks in economic growth. Two distinct approaches have emerged. In the first method, called the 'filter approach', the researcher identifies growth breaks on the basis of subjectively defined rules. Using this method, Hausmann, Pritchett, and Rodrik (2005) studies breaks in growth accelerations. The second method is based on statistical tests, which uses estimation and testing procedures to identify structural breaks. These approaches are based on the Bai-Perron (BP) methodology (Bai and Perron (1998)) which develops a general framework to estimate multiple structural changes occurring at unknown dates. Jones and Olken (2008) and Kerekes (2011) are among the earliest studies to use the BP methodology to study breaks in economic growth. Kar et al. (2013) discuss the shortcomings of each approach. Our method, which is developed in the next section, combines the statistical and filter approaches.

2.3 Methodology

In this section, we develop our method to detect turning points in tax/GDP ratios.

2.3.1 Descriptive statistics on levels of tax/GDP ratios

We start by descriptively examining the time-series of tax/GDP ratio in our study sample. Table 3.1 presents the average tax/GDP ratio by different regions and development level, and their evolution over time. Nearly all regions experienced growth in tax/GDP ratio over the time period in our sample, apart from South Asia.[3] While countries in the regions of East Asia & the Pacific, Europe & Central Asia, and Latin America & Caribbean experienced a steady increase, the Middle East & North Africa and the North American region remained pretty steady with some fluctuations around their average tax/GDP ratio.

When we classify countries by development level, we note that countries at all levels of development experience an average growth in tax/GDP ratios over the time period spanning the entire sample period. In the context of these long-run increases, we focus on growth spells and slumps, ie, accelerations and decelerations, by studying breaks in the growth rate of tax/GDP ratio. We test for stationarity of the growth in tax/GDP ratio using the method proposed in Carrion-i-Silvestre, Kim, and Perron (2009).[4]

[3]While our complete dataset includes 6 countries in South-Asia, in Table 3.1, we use a balanced sample of countries for which we have data for all five decades. Most of the decline in the tax/GDP ratio for South Asia is driven by Sri Lanka.

[4]Considerable research on identifying unit roots against a stationary process in time-series data with structural breaks has been conducted. Perron (1989) showed that standard Dickey and Fuller unit root tests can not reject the unit root null hypothesis when the process is trend stationary which contains a (known) break. Kim and Perron (2009) built a method to test for stationarity that allows a break at an unknown time under both the null and alternative hypotheses. Carrion-i-Silvestre, Kim, and Perron (2009) extended this methodology to allow for multiple breaks in the stationarity test. We use the code provided

2.3.2 Method to detect turning points in tax/GDP growth rates

Statistical estimation of structural breaks

The first step in our method is to apply a variant of a procedure proposed by Bai and Perron (1998), Bai and Perron (2003a) and adapted by Berg, Ostry, and Zettelmeyer (2012) and Kar et al. (2013), for the estimation of (multiple) breaks in the growth rate of tax/GDP ratio.

Following the framework provided in Bai and Perron (1998), we study the growth rate in tax/GDP ratio at time t, g_t, within a country as:

$$g_t = \mu_j + \epsilon_t, \qquad j = 1, ..., k+1 \tag{2.1}$$

where μ_j is the mean growth rate in tax/GDP ratio during regime j and k are the breakpoints in the time series.

Conceptually, the Bai-Perron method follows a two-part approach where it (i) tests the null hypothesis of no break against the alternative of an unknown number of breaks, and (ii) tests the null of k breaks against the alternative of k+1 breaks. The algorithm first searches all possible sets of breaks in the growth of tax/GDP ratio. Next, it determines for each number of breaks, k, the year that experienced the break, and the corresponding confidence interval.

The approach provides an asymptotically valid test for the presence of breaks, a consistent break date estimator, and a break date confidence interval with correct asymptotic coverage. Subsequent work by Jones and Olken (2008) and Bai and Perron (2003a) present Monte Carlo results for finite samples and find that the test is fairly conservative and does not capture every break in their simulated exercise. Given the low power of the Bai-Perron method for detecting relatively small changes in tax/GDP growth rates, the

by Carrion-i-Silvestre, Kim, and Perron (2009) to test for stationarity of growth in tax/GDP ratio.

list of breaks identified is not meant to be exhaustive, but rather we aim to identify major growth accelerations (decelerations) with high certainty.

Adding economic criterion to turning points

Our second step is to add 'filters' in order to focus on the most economically meaningful break points. We follow the Bai-Perron 'trimming' parameter, expressed as a percentage of the number of observations, which helps select the minimal number of observations in each segment between consecutive breaks. This minimum inter-break period is an important choice variable for our analysis. Imposing a longer period could lead to a type 1 error of missing an important break when it is truly present. But a smaller trimming parameter would reduce the power to reject the null of no additional break because the size of the test is smaller. It would allow more breaks but comes at the cost of picking up abrupt movements in the tax/GDP ratio so it is more likely to pick up movements due to short-term volatility. For our main results, we focus on a specification with 15% trimming parameter (roughly 8 years inter-break period). We run our analysis using a 10% trimming parameter (roughly 5 years inter-break period) as well. We also require that our breaks are bounded away from the sample endpoints by at least 3 years and replicate the analysis with 5 and 8 years (similar to our trimming parameter values). Critical values were adjusted according to values provided by Bai and Perron (2003b).

Next, we employ a series of additional economic criteria. Given the volatility in growth in tax/GDP ratio varies substantially across countries, employing just a statistical approach could also risk too many spurious breaks, particularly in countries with higher growth volatility. We focus on *significant* breaks in fiscal performance, which we define to be break points that are immediately followed by a period of at least 1 percent absolute annual growth in tax/GDP ratio. This allows us to identify systematically significant growths in tax/GDP ratios across countries. We explore other thresholds like 2 percent absolute annual average growth in tax/GDP ratio in the post-break period.

Classifying breaks into acceleration or deceleration

We classify these significant breaks as either *accelerations* or *decelerations* depending on whether the average growth rate in the tax/GDP ratio after the break is above or below the average growth rate before. Specifically, if $(g_{k+1} + .. + g_{k+8})/8$ is greater (less) than $(g_{k-1} + .. + g_{k-8})/8$, that is classified as an acceleration (deceleration).

Persistence of turning points

In addition to the benchmark definition of break points, we also explore *persistent* turning events. This is because an acceleration episode that is followed shortly by a sharp deceleration period may not be a particularly useful growth acceleration for analysis of longer-term growth changes in tax/GDP ratio. We classify acceleration (deceleration) episodes that are not followed by a deceleration (acceleration) break within the next ten years, as persistent breaks. We also explore persistent turning points over a 15-year horizon. Finally, we separately identify incomplete spells as acceleration periods that occur within ten years of the end of the sample.

2.3.3 Data

Our data comes from the publicly available data-set on tax revenues, factor shares and national income components, which can be retrieved at https://globaltaxation.world. The data-set was developed by Bachas et al. (2022) in a study on the impact of globalization on the effective taxation of capital and labor. As mentioned in the introduction, this data-set is advantageous for our purposes because it features both a broad coverage (150 countries between 1965 and 2018) and comprehensive measure of total taxes.

When available, OECD Revenue Statistics is the preferred source of data in the data-set, because it covers and classifies all types of tax revenues, usually back to 1965 for OECD countries. OECD data accounts for 41% of the country-year observations in the sample. Its main drawback is its limited coverage of non-OECD countries: in total it covers 93 countries, and only over the past two decades. To increase coverage, the

OECD data is augmented with tax revenue data from the ICTD/UNU-WIDER (17% of observations). This dataset achieves near worldwide coverage but only starts in the 1980s. To address these shortcomings, the data-set also draws on historical public finance data from government reports, primarily from the Harvard Library archives (30% of country-year observations) and from the 2005 version of the IMF GFS (offline historical database; 10% of observations).[5]

Throughout this paper, our main focus is on overall tax collection, which excludes non-tax sources of revenue (including from natural resources). Following Bachas et al. (2022), we relate total taxes collected to net domestic product (as opposed to national income). This relates tax collection to the appropriate measure of the domestic output base; results using national income are very similar in practice (available upon request).

2.3.4 Discussion and illustration of turning points in selected countries

Confounding GDP cycles

An important concern is that our estimated turning points may coincide with GDP growth cycles. This concern applies to both accelerations and decelerations. In this case, our captured breaking points would systematically reflect the country's business cycle.

Alleviating this concern is one of the main reasons we combine the statistically detected breaks with economic filter criteria. This combined approach allows us to filter out year-to-year volatility and focus on sustained growth episodes. Moreover, we will find that the results based on our benchmark method are consistent to instead using persistent turning points. These events, which are sustained for over a decade, are less likely to purely reflect the country's GDP cycle. Given that our outcome is the growth rate of tax/GDP, changes in GDP growth rates would have to be sustained over very long times;

[5] We note that the ICTD/UNU-WIDER data-set is, in turn, largely drawn from the online version of the IMF Government Finance Statistics. The additional use of IMF data is restricted to the offline historical data-set, which covers 1972-89 and fills gaps from the OECD and historical archives data.

for example, an initial recession would have to continue to worsen over long periods in order to trigger a turning point that reflects a sustained change in growth rate of tax/GDP.

While we consider our parameter choices to be conservative and make it less likely that turning points are entirely *confounded* by a country's GDP cycle, it is still possible that transitions between GDP cycles *trigger* turning points. This could, for example, be the case if certain determinants of turning points, such as tax policy reforms, have a partly cyclical component but the effects of the reform last longer than the initial cycle. In Section 2.5, we investigate this possibility by studying whether the timing of accelerations and decelerations is correlated with a country's GDP cycle being in the 'good times' or 'bad times' (based on Vegh and Vuletin, 2015).

Selected turning points: Illustrating the method

We illustrate our methodology with examples of four countries (Philippines, Turkey, Bangladesh, and Argentina) that experienced a minimum of 2 breaks in our study sample (Figure 2.1). The figure plots the tax/GDP ratio for each country (black lines). These countries allow us to explore breaks for countries with a range of tax/GDP values with Bangladesh starting with tax/GDP ratio of about 0.05 in the 1970s to Turkey and Argentina which were in the 0.15 range. We overlay the breakpoints with blue lines for accelerations and red lines for deceleration episodes.

The first break identified for the Philippines is an acceleration episode in 1983 which is followed by a deceleration episode in 1996 when the growth spell ends and the tax/GDP growth stagnates. Both the acceleration and deceleration episodes persist for at least ten years, but only the deceleration persists for over 15 years. The statistical approach using the Bai-Perron method finds another break point in 1975 but that does not meet our criteria of a minimum 8-year inter-break period and a large significant break of at least 1% absolute growth in tax/GDP after the break. Turkey experiences a similar acceleration episode in 1984 followed by a deceleration episode in 2001. Both breaks in this scenario are persistent for over 15 years. Bangladesh experiences 3 breaks during our study sample, an acceleration episode in 1983 followed by a deceleration in 1992 and another acceleration episode in 2000. The final acceleration is considered persistent as it leads to sustained significant growth in the tax/GDP ratio. Finally, in contrast to Bangladesh, Argentina starts with a deceleration episode in 1973 followed by an acceleration episode in 1983 and a deceleration in 2009. The acceleration episode in 1983 which raises the tax/GDP ratio from 0.10 to 0.33 to 2009 is persistent for over 15 years.

2.4 Results

2.4.1 Prevalence of turning points

In this sub-section, we describe the results of applying the method to detect turning points in the global and historical sample. Table 2.2 shows the number of breaks and their magnitudes, by region, development level, and decade of the sample.

To begin, we note that, despite somewhat conservative criteria in our benchmark setting, the method yields a large number of break points – 238 across all countries and years. It is interesting that these events are almost evenly spread between accelerations (116 turning points) and decelerations (122), meaning countries experience both frequent and sustained increases as well as stagnations in the tax revenue available to fund government activities. Approximately half of both accelerations (55) and decelerations (59) occur in low and lower-middle-income countries (LMICs). This high share of cases is partly due to the fact that country-year observations in those countries are a large share of the overall data-set, and we convert the numbers to probabilities below. Looking at the regional distribution, there are numerous accelerations (39) as well as decelerations (44) in sub-Saharan Africa as well as in Central and South America (respectively 21 accelerations and 27 decelerations).

We identify 24 countries with no breaks that meet our break criteria, 58 countries with exactly 1 break, 38 countries with 2 breaks, 24 countries with 3 breaks, and 8 countries with 4 breaks. Acceleration episodes can be isolated events not followed by another event (67 accelerations), followed by a deceleration break (30 breaks), or even succeeded by another acceleration spell (19 breaks). Similarly, half the deceleration episodes (61) are not followed by another break, 37 are followed by an acceleration, and 24 by another deceleration episode.

The confidence intervals for the breaks are fairly narrow - roughly 75% of the confidence interval are 2 years, another 11 % are 4 years, and only 3% are as wide as 10 years. This is partly because we choose a conservative trimming parameter and economic criteria of fairly large breaks.

Apart from the sheer number of events, Table 2.2 also illustrates the large magnitudes of the changes in tax/GDP during these turning points. Conditional on an increase of at least 1 percentage point average annual growth rate, the average acceleration in LMICs featured a staggering 12.5 average growth rate in tax/GDP. Interestingly, the magnitude of the growth-rate change seems to be decreasing in the development level, with the average post-acceleration growth rate being 11% in upper-middle income countries and 5.7% in high-income countries. Average post-acceleration growth rates are highest in Central and South America (15.6%), in Sub-Saharan Africa (12.2%) and in the Middle East and North Africa (11%); they are lowest in Europe and Central Asia (2.7%). Turning to decelerations, we note that the magnitude of the drop in tax/GDP growth rates is smaller (in absolute terms) than for accelerations. In LMICs, for example, the average growth rate in the post-deceleration years is -3.1%. These numbers would suggest there is 'more upside' to accelerations than there is 'downside' to decelerations

In Table 2.3, we calculate the observed likelihood of accelerations and decelerations, by dividing the number of episodes of each type by the number of country-years in which an episode could have occurred. The latter is calculated by summing up all country-years in our sample and eliminating a 7-year window after the occurrence of each episode, since our method considers this period as belonging to the same event. We also remove the first three years and final years of the sample for each country. Applying this rule separately by type of turning point, we obtain a number of possible country-years in which an acceleration could occur and a number of possible country-years in which a deceleration could occur. We divide the actual number of episodes by these observations to capture the observed likelihood of each type of event occurring.

Based on these calculations, the average likelihood of an acceleration starting in a given year is 3.27% in LMICs; 2.72% in upper-middle income countries; and, 2.24% in high-income countries. For decelerations, the numbers are 3.50% in LMICs; 3.30% in upper-middle income countries; and, 1.97% in high-income countries. For both types of turning points, there seems therefore to be a negative development-gradient in the likelihood of occurrence. Combined with the information from Table 2.2, when compared to HICs, LMICs are therefore both more likely to incur sustained upturns and downturns and the tax/GDP changes induced during these events are larger (in % terms). Turning to geographical differences, south Asia now appears as the region where a country at any point in time is most likely both to experience a sustained upturn (4.48%) and to experience a sustained downturn (5.22%).

Finally, Table 2.3 displays the likelihoods by decade (and region or development level). When studying turning events by decade, it is worth keeping in mind that the final decade (2010-2018) has fewer observations because of our requirement to have at least three post-event years (the last feasible year is 2015). Furthermore, certain cells of decade-region have much fewer underlying observations than others, which in turns creates volatility in the calculated probabilities - see, for example, the 16.67% likelihood of a deceleration in North America in the 2000-2010 decade which reflects the well-known experience of a limited number of countries in that region during that period. With these caveats in mind, there are a few trends that appear, though they are not striking. Somewhat broadly across development groups, accelerations appear less likely in more recent times (2000-2018) than in the earliest decades (1960-1980); the same is broadly true for decelerations. At the same time, when inspecting trends by region, perhaps what stands out the most is the strong heterogeneity in experiences. For example, sub-Saharan Africa has witnessed a general decline over decades in the frequency of decelerations and an uptick in the likelihood of observing accelerations (with the exception of the most recent 2010-2018 period); the region of East Asia and Pacific has experienced increases and decreases over time in both decelerations and accelerations; the region of Central and South America witnessed a peak in the occurrence of both accelerations and decelerations in the decade 1980-1990, and a steady decline in the likelihood of both types of turning points since then.

2.4.2 Persistence of turning points

In our benchmark, we require a period of 8 years between potential successive breaks. It is, however, entirely possible that breaks are sustained for longer than this 8-year period. Also, a persistent acceleration period could be followed by another acceleration beyond the minimum inter-break period (and similarly for persistent decelerations which can be followed by another deceleration episode). In this sub-section, we investigate the extent to which our detected breaks are persistent (following the definition in Section 2.3). The results are reported in Table 2.4.

We are interested in studying the share of initially detected breaks that are persistent over these longer horizons of 10 and 15 years. In order to do this, we first have to count the number of 'incomplete spells': turning points that are detected within 15 years of the end of a country's sample. These incomplete spells, which are reported in the final column of Table 2.4, could not, by construction, be potentially persistent for 15 years. Intuitively, the sample of breaking points that can be persistent is then the initial set of turning points minus the incomplete spells.

One first observation which emerges from Table 2.4 is that, conditional on a break point being persistent for 10 years, this same spell is very likely to be persistent for 15 years. Therefore, we focus directly on the conversion rate from initial break points to 'very persistent' break points. Studying differences across development level, we observe that the share of accelerations that persist for at least 15 years is: 58% in LMICs; 50% in upper-middle income countries; and, 45% in high-income countries. The share of decelerations which are persistent for at least 15 years are: 47% in LMICs; 56% in upper-middle income countries; and, 65% in high-income countries. In other words, conditional on a deceleration, the likelihood of a sustained downturn is larger at higher levels of development; in contrast, the likelihood of a persistent upturn in tax performance (conditional on an acceleration) is larger at lower levels of development.

Turning to regional differences, certain regions stand out as having particularly large rates of conversion from initial breaks to persistent turning points. For example, 62% of accelerations and 56% of decelerations persist for at least 15 years in Latin America; in sub-Saharan Africa, 59% of accelerations and 44% of decelerations persist for at least 15 years. Combined with the findings from Tables 2.2-2.3 that these are also the groups with some of the highest likelihoods of breaks occurring in the first place and the largest post-break magnitudes of tax/GDP changes, these are therefore regions with remarkably dynamic tax collection performances over the past 5 decades.

2.4.3 Robustness

As discussed in Section 2.3, we employ a series of robustness exercises for the key parameter choices in our methodology to estimate breaks.

One important methodological choice is the minimum size of post-break growth in the tax/GDP ratio. Due to varying growth volatility in these ratios across countries, this choice allows us to identify significant breaks across all countries. Our benchmark criteria was 1 percent absolute annual growth in tax/GDP in the post-break period. In Table 2.A.1, we alternatively consider turning points as breaks points that are immediately followed by a period of at least 2 percent absolute annual growth in tax/GDP ratio. This results in a drop in the set of breaks from 238 under 1 percent criterion to 196 under the 2 percent criterion. Interestingly, most of the drop comes from deceleration episodes which reduce to 90 episodes.

As a second robustness, we repeat the exercise with a smaller trimming parameter in the Bai-Perron method. A smaller trimming parameter leads to a smaller minimum inter-break period in our set of breaks. We run our analysis using a 10% trimming parameter which corresponds to roughly 5 years inter-break period. Table 2.A.2 shows the number of breaks and their magnitudes, by region, developmental level, and decade for a 10% trimming parameter. As expected, a smaller trimming parameter identifies a much larger set of breaks, taking the total to 340 break points across all countries and years. Interestingly, the split between acceleration and deceleration episodes is roughly equal even with a smaller trimming parameter – we identify 171 acceleration episodes and 169 decelerations. Lower-middle income countries continue to account for roughly half of both the accelerations (83) and decelerations (84).

2.5 Predictors of turning points

2.5.1 Set-up

In this section, we analyze the predictability of turning points in tax performance. Specifically, we study if a standard set of political and economic variables statistically predict the timing of turning points – both accelerations and decelerations. Our empirical framework captures empirical associations between changes in these explanatory variables and the onset of turning points, which may in turn serve as a starting point for causal investigations. Moreover, the broad coverage of our underlying tax data-set limited the set of potential explanatory variables which had similarly broad coverage; as such, these results can contribute to future work on the precise mechanisms through which broad economic and political factors trigger turning points in tax/GDP.

Our empirical framework estimates the likelihood of observing a turning point as a function of different explanatory variables. Using probit, we estimate variants of the following model:[6]

$$P(Turningpoint_{ct}|X) = \Phi(\theta_c + \beta \cdot X_{ct}) \tag{2.2}$$

where $Turningpoint_{ct}$ is a dummy for a turning point (acceleration or deceleration) in country c in year t, θ_c are country fixed effects and X_{ct} is the set of explanatory variables. More specifically, our outcome variable takes a value of 1 in the three years centered on the first year of the turning point. This is a similar specification to the analysis conducted in Hausmann, Pritchett, and Rodrik (2005) for turning points in GDP growth. The explanatory variables are either dummy variables for the onset of specific events or first-differences of continuous variables. As such, we estimate if *changes* in these explanatory variables within country over time are associated with the probability of a turning point occurrence. Note that the first-differencing amounts to estimating the model in levels of the explanatory variables with the inclusion of country-fixed effects. The year-fixed effects help to control for global trends in the likelihood of turning points' occurrence. Standard errors are clustered at the country level.

Intuitively, the estimated coefficients indicate if countries that experience turning points have differential changes within-country in specific explanatory variables relative to those 'control group' countries that do not have turning points in the same year.

We make the following adjustments to the estimation sample which sharpen the control group comparison. First, for each country, we drop the first and last three years of data, since breaking points could not have been calculated in those years as they are bounded away from our sample endpoints. Second, we drop all years pertaining to years

[6] The findings are robust to using logit instead (results available upon request).

$t+2,...,t+8$ of an episode, since we are interested in predicting the timing of the turning point.

We organize the explanatory variables in four categories

Category #1: Political changes: Our first variable in this category is the Polity V variable to measure changes in the political environment. The variable (in levels) ranges from -10 to +10, where more positive values indicate changes towards increased democratization. The Polity variable is primarily driven by the two sub-categories of political competition and executive constraint. In Section 2.5.4, we explore the role of each of these sub-categories. All country-year values between -10 and -1 are classified as 'autocratic', while all variables between 0 and 10 are 'democratic'. In our main specification, we take the first-differenced value in all country-years and in turn create a moving average of the first-differenced value, from t-2 to t+2 centered on year t. By using the moving average, we study if turning points occur in periods where the political conditions were generally worsening or improving. We similarly measure the moving-average of all other continuous explanatory variables. Changes towards democratization may trigger an acceleration event, for several reasons. For example, in the study of long-run historical experiences in European countries, Dincecco (2009) finds that reforms which curb the executive's discretionary power (which would be reflected in an increase in the Polity variable) were associated with dramatic increases in aggregate per capita revenues. Related, a significant number of theories in political science argue why democracies are able (or not) to extract higher taxes per capita than autocracies (including Cheibub, 1998; Ross, 2004; Aidt and Jensen, 2013). In robustness checks, we investigate different ways to capture both large positive and large negative changes in the Polity score, to reflect the non-linear theoretical predictions that relate democratization to changes in tax/GDP ratios.

Our second variable in this category comes from the Correlates of War database. We use both the year in which a violent conflict ends and the year in which a violent conflict begins. Conflict can be due either to inter-state or intra-state violence. The variable onset of violence takes a value of 1 in the three-year period beginning with the onset of a violent conflict; the variable end of violence takes a value of 1 in the three-year period beginning with the end of a violent conflict. Conflict may lead to a collapse of the state, which in turn could trigger a sustained deceleration. At the same time, the 'bellicist' theory of state building argues that politicians and rulers seek to extract resources from citizens to sustain the funding of protection against external forces. For example, historical studies have argued that the second world war, by creating a large increase in the demand for military spending, ushered in the modern income tax in the United States and Europe and contributed to a sustained increase in tax/GDP ratios.

Category #2: International economic changes The variables in this category capture changes in countries' cross-border activities. First, we measure trade openness as the share of imports and exports relative to GDP. This is a 'de facto' measure of openness, which reflects the impacts of both policy changes and changes in economic forces which lead to increased or decreased flows of goods and services across borders. Similarly to the Polity variable in the first category, the explanatory variable is the moving-average of the first-differenced variable. Second, we measure capital openness. Capital flows across borders can take numerous forms, and we focus on two dimensions: the sum of inward and outward FDI, expressed as a share of GDP; the sum of all foreign assets and liabilities, expressed as a share of GDP. We use the moving average of the first-differenced variables. These data are retrieved from the Openness Data database (Gräbner et al. (2020)).[7]

Large increases in cross-border openness may increase the mobility of certain factors of production, such as capital and skilled labor. In turn, governments may be forced to (permanently) lower their taxation of these factors, in order to prevent their flight. This mechanism is often referred to as the 'race to the bottom' and it could trigger a deceleration. Bachas et al. (2022) find that this effect appears to operate in developed

[7]Another possibility is to study de jure openness measures, which reflect government policies to restrict or stimulate cross-border flows. Such measures, including the Chin-Ito index, were uncorrelated with both decelerations and accelerations (results available upon request).

countries, but that trade openness causes a significant increase in tax/GDP in developing countries by increasing the share of economic activity in larger, corporate structures where tax enforcement is improved. Large increases in cross-border openness may therefore trigger the start of an acceleration, primarily in developing countries. In Section 2.5.4, we study the potential heterogeneity by development level in associations between timing of turning points and the explanatory variables.[8]

Category #3: Domestic economic changes Our third category captures changes in the domestic economic environment. The distinction between the second and third categories is not meant to be conceptual in any way, but simply a framework to organize the variables. We focus on three dimensions of the economic environment. First, we measure the yearly change in the inflation rate (moving average of the first-difference). This data comes from the World Bank Development Indicators. Tax systems that do not account for inflation may face a "bracket creep" during periods of high inflation (Mourre and Princen, 2019). This occurs when tax authorities collect more revenue due to higher prices, but do not adjust the tax base. Periods of particularly high inflation may trigger a turning point if the bracket creep maintains for a sufficiently long period of time. Second, we measure the yearly change in general government debt expressed as a share of GDP (moving average of the first-difference). The data comes from the IMF's Global Debt Database. Particularly high levels of debt may trigger a need for meaningfully higher levels of tax collection over a sustained period of time. At the same time, high levels of debt may trigger international intervention to countries - for example, in the form of assistance programs from the IMF or the World Bank. These programs may in turn induce tax reforms with the objective of collecting more taxes.[9] Third, as described in Section 2.3.4,

[8]We were interested in measuring changes in global commodity prices, combined with information on the importance of various commodities for a country's imports and exports (going beyond natural resource richness). We were not able to find a database with these measures which was comparably comprehensive in coverage as our tax/GDP data.

[9]We were interested in studying IMF assistance programs as an independent explanatory variable. The data-coverage is, however, narrow compared to our tax/GDP data and we decided to not include it in the main analysis for this reason. In results not shown, we find that an active crisis or non-crisis IMF

we study if the onset of accelerations or decelerations are associated with a country being in either the 'good times' or the 'bad times' of its GDP cycle, compared to its 'normal times'. We measure the GDP cycles separately by country based on the method developed in Vegh and Vuletin (2015). Specifically, we first estimate the country-specific real GDP cycles. In turn, ‘bad times’ takes a value of 1 if the GDP cycle falls in the bottom tercile of the country-specific GDP cycles and 0 otherwise; ‘good times’ takes a value of 1 if the GDP cycle falls in the top third of GDP cycles. In the regression, these cycles will be compared to the omitted group, the ‘normal times’ where cycles fall in the middle tercile of the country-specific distribution.[10]

Category #4: Tax reforms Since our interests is in studying turning points in tax collection, it is natural that we are interested in the predictive power of reforms to tax instruments.[11] There are, however, limited data-sets that contain information on statutory dimensions of the main tax bases for as large a set of countries and years as our sample. Therefore, we limit our focus to VAT implementation: the explanatory variable takes a value of 1 in the three-year period beginning with the year where the VAT was first implemented (based on data in Keen and Lockwood, 2010). The rise of VAT adoption is one of the most significant global tax reform trends since the 1960s. Moreover, the VAT is a significant source of tax revenue, particularly in developing countries. As such, VAT adoption is a plausible candidate for a tax reform which may have triggered turning points during our sample-period. As noted, we are in principle interested in studying the impacts of a much broader set of tax reform tools and collection of the required data for such an exercise is left for future research.[12]

program is not associated with the onset of either accelerations or decelerations.

[10] In a robustness check, we alternatively investigate if the onset of turning points is correlated with particularly large changes in the country's moving-average real GDP growth rates.

[11] Other types of domestic government reform may be important, such as financial regulation. We found no strong associations when using the data on financial reforms from Detragiache, Abiad, and Tressel (2008).

[12] We explored using the data on rate changes to the VAT, personal income tax and corporate income tax from Vegh and Vuletin (2015). However, the sample size reduction is significant and we did not pursue this further.

Before turning to the results, we re-iterate that this exercise is not a causal investigation of the determinants of turning points, for at least two reasons. First, the empirical design is unlikely to rule out all unobservable confounders which determine the start of break points and which are correlated with the observed explanatory variables. Second, the explanatory variables remain too broad for a precise investigation of mechanisms.

2.5.2 Main results

Table 2.5 shows the results from estimating equation 2.2. We separately study the timing of accelerations (in Panel A) and decelerations (in Panel B). In a robustness check, we estimate the ordered probit for both sets of events. The first columns in each panel show the bivariate probit between the likelihood of a turning point and each of the explanatory variables described above.

Focusing on accelerations in Panel A, several results stand out. First, improvements in the political environment towards increased democratization are strongly predictive of increased likelihood of an acceleration. We will investigate this result further and find it to be remarkably robust. At the same time, changes in violence have the expected signs but they are not statistically significant (end of violence increases the likelihood of triggering an acceleration, beginning of violence decreases it). Second, changes in international economic factors seem to be important: increased cross-border capital flow has a large negative effect on the likelihood of an acceleration; cross-border flow of G-S appears to have a smaller effect, but this result is sensitive to specifications. Third, changes in 'domestic' economic factors have a limited association with the onset of positive turning points. Fourth, the implementation of the VAT is associated with an increase in the likelihood of an acceleration but is statistically insignificant – though this result will also be sensitive to specifications.

In the final column of Panel A, we simultaneously include all explanatory variables, which leads to a large drop in overall sample-size. In this multivariate probit model, we find: polity continues to have a strong and precisely estimated positive association; the end of violence has a large estimated effect, but it remains imprecise; the adoption of a VAT has a very large and positive impact on tax accelerations, which is now significant at the 5%. In summary, institutional factors and tax policies are more strongly correlated with sustained increases in tax performance, economic conditions less so.

Interestingly, the set of explanatory variables does a much poorer job at predicting the timing of decelerations (panel B). Changes in the political environment are not strongly associated with changes in the likelihood of triggering a sustained downturn in tax collection. Being in the 'good times' of the country's GDP cycle is marginally associated with an increased likelihood of observing a deceleration in the bi-variate probit, but this result does not survive in the multivariate probit; increased trade openness is associated with a lower likelihood of triggering a deceleration both in the bi-variate and multi-variate probit, but this result is only marginally significant. In summary, there seems to be much more unpredictability in decelerations than accelerations, at least relative to our set of explanatory variables.

2.5.3 Robustness checks

We provide two main robustness checks of our results.

Robustness #1: Alternative measures of break points

Our first robustness check investigates variation in the methodological choices to measure break points. We consider four alternative measures:

1. While our benchmark criteria was an absolute growth rate of at least 1 percent, we change it to 2 percent (see Section 2.4.3).

2. Our benchmark criteria imposes 8 years between breaks, and we vary it to 5 years in this robustness check (see Section 2.4.3).

3. We focus on accelerations and decelerations that persist for at least 15 years (see Section 2.4.2).

4. While our analysis has separated the study of accelerations and decelerations, we combine the two by creating an ordered variable. This variable takes a value of 1 in the case of an acceleration, a value of -1 in case of a deceleration and is equal to 0 otherwise. We use our benchmark definition of turning points to create this variable. In turn, we investigate the determinants of this variable using an ordered probit estimation model and the same set of explanatory variables.

In each of the first three robustness checks, we restrict the estimation sample following the same intuition as for the main benchmark (we drop the first and last three years for each country; we drop observations in the inter-break period).

The results are reported in Table 2.6. Focusing first on accelerations (columns 1 to 3), the results are qualitatively robust to using turning points which are larger in magnitude, though statistical significance of the variable for end of violence and VAT adoption are just outside conventional levels. When we focus on the timing of persistent accelerations, the coefficient on VAT adoption interestingly becomes both larger in magnitude and more statistically significant. Results using the shorter inter-break period are very similar to the benchmark specification. Turning to decelerations (columns 4-6), the main finding from previous analyses carries over: there is limited general consistency in coefficients, though increases in the debt variable continue to predict decreases in both large and persistent downturns. The results using the shorter inter-break period are similar to the benchmark specification. Finally, in column 7 we estimate the ordered probit, which pools acceleration and deceleration events in one outcome variable. Consistent with the prior results, the coefficient on the polity variable is positive, large and precisely estimated. The coefficients on trade openness and debt are also positive.

Robustness #2: Alternative measures of explanatory variables

In our main specification some explanatory variables captured discrete events and other variables captured continuous changes. In the second robustness check, we redefine all explanatory variables to capture large events as follows:

- For the polity variable, we define two large events: movement towards democracy takes a value of 1 during the three-year period starting with an increase in the polity variable by 3 points or more; movement towards autocracy takes a value of 1 during the three-year period starting with a decrease in the polity variable by 3 points or more. Here, the omitted category is the set of country-years with changes in the polity variable which are smaller than the threshold (including no yearly change).

- For each of the remaining continuous variables (inflation; debt; GDP; capital openness; trade openness), we first create the deciles of the first-differenced changes in the full sample. We then define two large events: a large positive change takes a value of 1 during the three-year period starting with a yearly change that belongs in the top decile; a large negative change takes a value of 1 during the three-year period starting with a yearly change occuring in the bottom decile. In this case, the omitted category is the yearly changes that fall in middle 8 deciles.

- The remaining variables (onset and end of violence; VAT adoption) remain as they initially were.

The results from estimating the multivariate probit using these large, discrete events is reported in Appendix Table 2.A.3. The results are mainly consistent with the results in 2.5. Focusing first on accelerations, changes in the political environment continue to have predictive power: both a large movement towards democracy as well as the end of a violent conflict significantly predict the beginning of a sustained increased increase in tax collection. The beginning of violence has an economically large, though insignificant, negative coefficient. The implementation of VAT has a remarkably large, positive association with the onset of an acceleration, and is significant at 10 percent. The remaining variables which proxy for large domestic and international economic events are mainly insignificant. Similar to Table 2.5, for decelerations the main finding is the unpredictability of these events. For the most part, the variables are imprecisely estimated. The only exceptions are the large increases in inflation and debt which are associated with a decreased likelihood of a sustained downturn in tax collection, which may be slightly counter-intuitive.

2.5.4 Further analyses

To complete this section, we provide two additional investigations of the results.

Extension #1: Probing the Polity V result

In the first exercise, shown in Table 2.A.4, we probe further the intriguing polity result. In the first two columns, we find that the positive association between polity and the onset of an acceleration, as well as the absence of any association for decelerations, hold when we include country fixed effects. Since our benchmark specification is in first differences, the inclusion of these fixed effects controls for any country-specific differences in the changing likelihood of turning points.

In the following four columns, we unpack the polity variable into its two main components: political competition and executive constraint. The political competition score, in turn, is determined by the extent to which there are binding rules on when, whether and how political preferences by non-state actors can be expressed; and, the extent to which alternative preferences for policy and leadership can be pursued in the political space. The executive constraint variable depends on the extent to which there is regulation surrounding the recruitment of the chief executive, and the extent to which executive recruitment is competitive and open for all that are politically active. In bivariate probit regressions (columns 3-6), we find that both dimensions of the polity variable are positively associated with the likelihood of triggering an acceleration and unrelated with the onset of decelerations.

In the final columns, we investigate different measures of changes in the political environment. Columns 7-8 use the 'large events' studied in the multivariate model (Table) and replicate them here in the bivariate probit model. Columns 9-10 use the definition of transitions to democracy and autocracy used in recent work by Acemoglu et al. (2019) to study the effects of democratization on development. Specifically, 'democratic transition' takes a value of 1 in the three years beginning with the year where the country's polity score crosses from a negative value to a weakly positive value; 'autocratic transition' takes a value of 1 in the three years beginning with the year where the country's polity score crosses from a weakly positive value to a strictly negative value. These events are fairly rare in the data. Using these (rare) political events, we find that: transition to democracy has a very large and precisely estimated positive association with sustained increases in tax collection, but an autocratic transition has no association; neither of these large political changes have any association with statistically precise association with downturns.

Extension #2: Heterogeneity by development level

In the second investigation, we study if there are differences in the associations by development level. The purpose of this exercise is to uncover statistical patterns, which in turn could be starting points for formal (causal) and in-depth analyses. As such, we simply inspect whether there are differences by development level in the regression coefficients based on the bivariate probit association between turning points and the explanatory variables in Table 2.5.

The results are shown in Figure 2.2. Each panel in the graph focuses on a different explanatory variable; the left-side shows the correlation coefficient for accelerations, by separately development level, and the right-side shows correlations for decelerations, also separately by development level.

Starting with the polity variable in panel a), we see that the positive association with accelerations exists in both LMICs and HICs, through the magnitude is almost twice as large in HICs. The end of violent conflict is associated with an increased likelihood of accelerations in HICs, with a null association in LMICs (panel b). In panel c), we find that there are no precise bi-variate associations with VAT adoption in any sub-sample; recall that the significance of this variable emerged in the multivariate probit model.

In panel d), increases in inflation seem to be both positively associated with accelerations and negatively associated with decelerations in HICs, while the associations are precisely estimated to be null in LMICs. Increases in debt are associated with a decrease in the likelihood of decelerations in HICs (panel e), though this may reflect government's need to fund future debt payments with tax revenue. In panel f), we intriguingly find that 'good times' of the country's GDP cycle are associated with an increased likelihood of decelerations in LMICs.

In panel g), another intriguing pattern emerges: limited to HICs, increased cross-border openness to capital flows has a strong, negative association with the onset of an acceleration. This is consistent with the notion that globalization, by increasing cross-border capital mobility, constrains the size of government in HICs. In contrast, in panel h), we find that increased cross-border flow of goods and services is both positively associated with accelerations and negatively associated with decelerations, but only in LMICs. This finding is consistent with the results in Bachas et al. (2022).

In summary, these bi-variate associations suggest interesting heterogeneity patterns: some economic forces, particularly related to international openness, may have different impacts on turning points in HICs vs LMICs; at the same time, improvements toward democratization are strongly associated with sustained increases in tax collection at all development levels.

2.6 Conclusion

In this paper, we implement a method to detect turning points in tax/GDP ratios in a large sample of countries covering the past 5 decades (1965-2018). By organizing the data around turning points in tax performance, our study provides findings that (partly) address questions which are likely to preoccupy policy-makers in many countries around the world, such as: how likely is it that a country undergoes a period of sustained increase in tax collection?; what policies or other factors correlate with the timing of such events?; is a country as exposed to upturns as to downturns in tax performance, and what can be done to minimize the likelihood of downturns?

Our analysis yields three sets of results. First, accelerations and decelerations are prevalent. For example, the likelihood that a developing country will begin an acceleration in tax/GDP at any point in time since 1965 is 3.27%. Developing countries are both more likely to experience tax accelerations than developed countries and the post-acceleration increases in tax/GDP are (much) larger in magnitude. Interestingly, decelerations are about as frequent as accelerations, but the drop in tax/GDP is smaller in (absolute) magnitude. Second, many turning points are very persistent and last at least 15 years; this is true both for accelerations and for decelerations. While the likelihood of a sustained deceleration, conditional on a deceleration, is larger at higher levels of development, the likelihood of experiencing a persistent upturn (conditional on an acceleration) is larger at lower levels of development. Third, changes in the political environment towards democratization are strongly associated with increases in the likelihood of triggering an acceleration, at all levels of development. Certain economic variables, as well as tax reforms such as the introduction of VAT, have some predictive power for accelerations, but the results are not decisive. Finally, the set of explanatory variables does a much poorer job at predicting decelerations than accelerations.

We emphasize that the exercise to predict the onset of turning points is both correlational in nature and faces data-limitations related to the exact mechanisms. It may be the case that an improved research design provides clearer insights on the role that economic factors play in triggering turning points. Given the importance of improving tax collection in a sustained manner for many countries around the world, the search for the causal determinants of turning points, be they common or specific to certain countries in certain settings, is an interesting area for future research.

2.7 Acknowledgements

This chapter, in part has been submitted for publication. Goyal, Radhika; Jensen, Anders. The dissertation author was the primary investigator and author of this material.

2.8 Figures and Tables

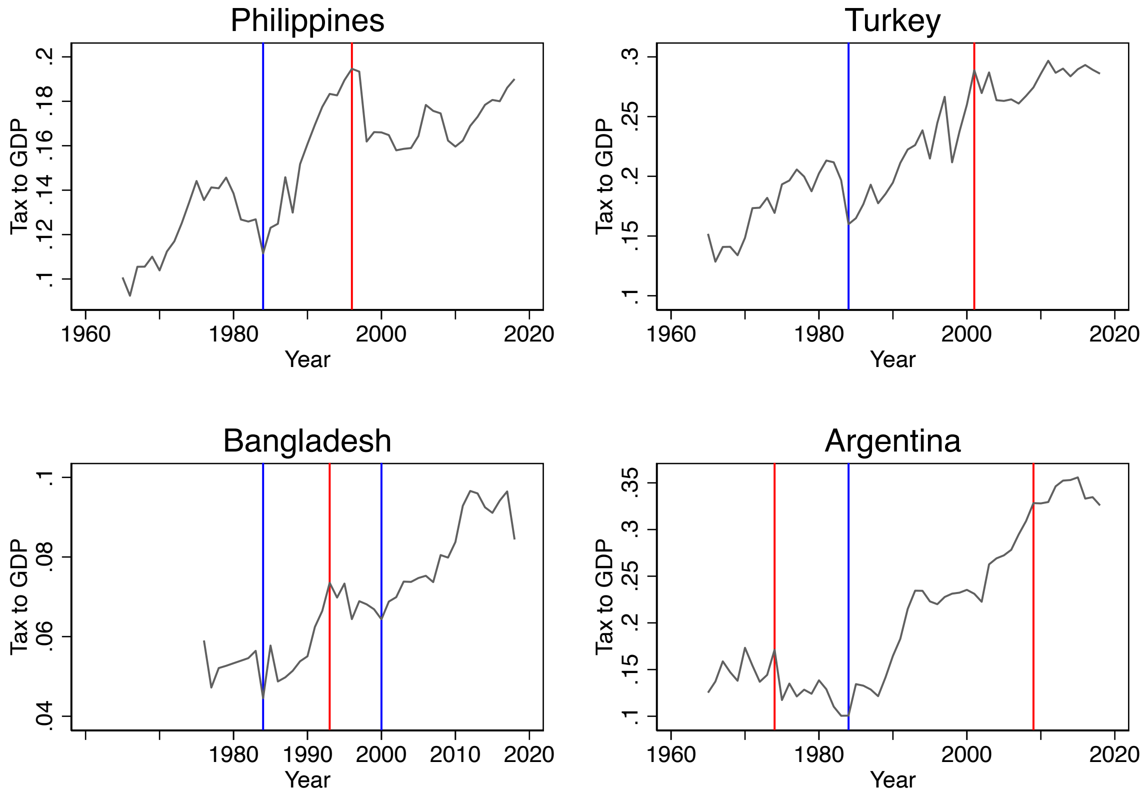


Figure 2.1. Examples of tax/GDP growth episodes

Notes: The black line denotes the tax/GDP during our sample period. Acceleration and deceleration episodes are represented by blue and red lines respectively. For more details, see Section 2.3.

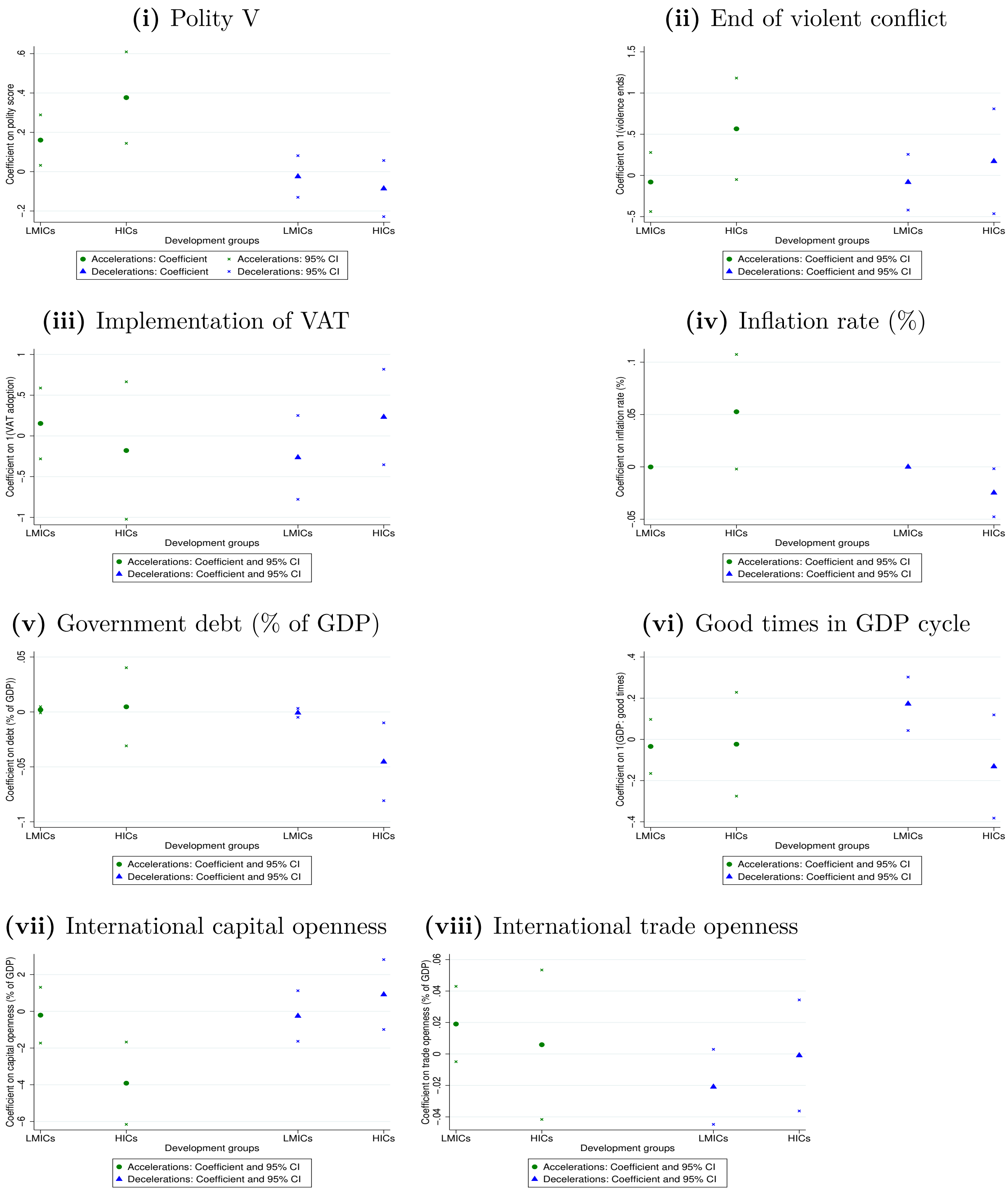


Figure 2.2. Heterogeneity by level of development

Notes: These panels present bi-variate probit estimations of the onset of an acceleration (in green circles) and the onset of a deceleration (in blue triangles). Across panels, the explanatory variable differs. The bi-variate analyses are conducted separately by development group: low and middle income countries (LMICs) and high-income countries (HICs). For more details, see Section 2.5.4.

Table 2.1. Summary statistics of tax to GDP ratio

		Average Tax to GDP (by decade)				
Region	No of Countries	1970-1980	1980-1990	1990-2000	2000-2010	2010-2018
LIC & LMIC	45	0.14	0.14	0.13	0.15	0.17
Upper middle income	24	0.15	0.17	0.18	0.20	0.21
High income	37	0.30	0.32	0.33	0.34	0.35

		Average Tax to GDP (by decade)				
Income Groups	No of Countries	1970-1980	1980-1990	1990-2000	2000-2010	2010-2018
East Asia & Pacific	11	0.19	0.21	0.22	0.22	0.23
Europe & Central Asia	20	0.34	0.39	0.41	0.43	0.44
Latin America & Caribbean	24	0.15	0.17	0.17	0.20	0.22
Middle East & North Africa	12	0.17	0.16	0.15	0.16	0.17
North America	2	0.32	0.34	0.37	0.35	0.34
South Asia	3	0.16	0.17	0.17	0.15	0.15
Sub-Saharan Africa	34	0.14	0.15	0.14	0.15	0.17

Notes: The table shows the average tax to GDP ratio in the sample categorized by region in the top panel and by income groups in the lower panel. The development categories are based on the World Bank's income classification. Income categories low income and low middle income have been combined. We keep a balanced sample of countries for which we have data starting before 1975. Tax to GDP ratio includes – personal income taxes, corporate income taxes, social security payroll taxes, property taxes, wealth taxes, estate and inheritance taxes, consumption, and other indirect taxes – at all levels of government as a proportion of national GDP.

Table 2.2. Tax to GDP growth breaks by decade and income classification

	Breaks	Average growth in T/Y pre-break	Average growth in T/Y post-break	Number of breaks (by decade) 1970-1980	1980-1990	1990-2000	2000-2010	2010-2018
				Panel A: Accelerations				
Region								
East Asia & Pacific	16	-1.2	8.4	1	5	2	5	3
Europe & Central Asia	20	0.3	2.7	5	2	3	4	6
Latin America & Caribbean	21	-1.5	15.6	5	9	5	2	0
Middle East & North Africa	14	-3.0	11.0	3	3	2	5	1
North America	0	-	-	0	0	0	0	0
South Asia	6	-0.4	4.9	0	3	0	2	1
Sub-Saharan Africa	39	-1.8	12.2	4	9	12	13	1
Income Groups								
LIC & LMIC	55	-1.8	12.5	6	17	12	16	4
Upper middle income	28	-0.7	11.0	4	6	6	8	4
High income	33	-1.2	5.7	8	8	6	7	4
				Panel B: Decelerations				
Region								
East Asia & Pacific	11	3.6	-0.3	2	1	3	2	3
Europe & Central Asia	18	2.6	-0.1	2	5	3	7	1
Latin America & Caribbean	27	4.2	-2.5	6	7	7	6	1
Middle East & North Africa	12	14.2	-3.2	2	3	4	3	0
North America	3	1.2	-0.6	1	0	1	1	0
South Asia	7	2.2	-1.5	2	1	4	0	0
Sub-Saharan Africa	44	11.0	-4.1	13	14	7	5	5
Income Groups								
LIC & LMIC	59	9.0	-3.1	16	15	14	8	6
Upper middle income	34	4.9	-2.0	7	7	7	10	3
High income	29	6.2	-1.7	5	9	8	6	1

Notes: The table shows the total number of breaks in the growth of the tax-to-GDP ratio and the average growth in tax-to-GDP ratio before and after the break for acceleration and deceleration episodes. We estimate the 8-year average before and after break. Countries have been categorized by region and income groups. The development categories are based on the World Bank's income classification. Income categories low income and low middle income have been combined.

Table 2.3. Likelihood of Tax to GDP growth breaks by decade and income classification

	Breaks	Average growth in T/Y		Probability of breaks (by decade)				
		pre-break	post-break	1970-1980	1980-1990	1990-2000	2000-2010	2010-2018
				Panel A: Accelerations				
Region								
East Asia & Pacific	3.04%	-1.2	8.4	1.08%	4.59%	1.80%	3.68%	3.85%
Europe & Central Asia	1.74%	0.3	2.7	3.13%	1.27%	1.23%	1.08%	2.73%
Latin America & Caribbean	2.70%	-1.5	15.6	3.16%	6.47%	3.25%	0.96%	0.00%
Middle East & North Africa	3.65%	-3.0	11.0	3.85%	4.55%	2.11%	4.90%	2.33%
North America	0.00%	-	-	0.00%	0.00%	0.00%	0.00%	0.00%
South Asia	4.48%	-0.4	4.9	0.00%	12.50%	0.00%	5.26%	3.57%
Sub-Saharan Africa	3.42%	-1.8	12.2	1.73%	4.00%	5.36%	4.28%	0.65%
Income Groups								
LIC & LMIC	3.27%	-1.8	12.5	1.81%	5.70%	3.63%	3.43%	1.56%
Upper middle income	2.72%	-0.7	11.0	2.26%	3.92%	2.58%	2.81%	2.20%
High income	2.24%	-1.2	5.7	3.11%	2.78%	2.02%	1.70%	1.84%
				Panel B: Decelerations				
Region								
East Asia & Pacific	2.09%	3.6	-0.3	2.15%	0.92%	2.70%	1.47%	3.85%
Europe & Central Asia	1.56%	2.6	-0.1	1.25%	3.16%	1.23%	1.90%	0.45%
Latin America & Caribbean	3.47%	4.2	-2.5	3.80%	5.04%	4.55%	2.88%	0.84%
Middle East & North Africa	3.13%	14.2	-3.2	2.56%	4.55%	4.21%	2.94%	0.00%
North America	4.23%	1.2	-0.6	6.67%	0.00%	5.00%	16.67%	0.00%
South Asia	5.22%	2.2	-1.5	6.45%	4.17%	30.77%	0.00%	0.00%
Sub-Saharan Africa	3.86%	11.0	-4.1	5.63%	6.22%	3.13%	1.64%	3.23%
Income Groups								
LIC & LMIC	3.50%	9.0	-3.1	4.82%	5.03%	4.23%	1.71%	2.34%
Upper middle income	3.30%	4.9	-2.0	3.95%	4.58%	3.00%	3.51%	1.65%
High income	1.97%	6.2	-1.7	1.95%	3.13%	2.69%	1.46%	0.46%

Notes: The table shows the probability of breaks in the growth of the tax-to-GDP ratio and the average growth in tax-to-GDP ratio before and after the break for acceleration and deceleration episodes. The probability of a break is estimated by dividing the total number of breaks by the number of country-years in which the break could have occurred (estimated using total number of country-years in the sample and eliminating the 7 year period after every break). We estimate the 8-year average before and after break. Countries have been categorized by region and income groups. The development categories are based on the World Bank's income classification. Income categories low income and low middle income have been combined.

Table 2.4. Persistence of breaks

	Countries	Breaks	Persistent for		Incomplete
			>10 yrs	>15 yrs	spells
		Panel A: Accelerations			
Region					
East Asia & Pacific	19	16	11	8	5
Europe & Central Asia	44	20	11	8	10
Latin America & Caribbean	26	21	14	13	2
Middle East & North Africa	15	14	11	7	5
North America	2	0	0	0	0
South Asia	6	6	3	2	2
Sub-Saharan Africa	40	39	31	23	11
Income Groups					
LIC & LMIC	63	55	42	32	15
Upper middle income	41	28	20	14	10
High income	48	33	19	15	10
		Panel B: Decelerations			
Region					
East Asia & Pacific	19	11	8	6	4
Europe & Central Asia	44	18	15	11	5
Latin America & Caribbean	26	27	21	15	6
Middle East & North Africa	15	12	12	8	3
North America	2	3	3	3	0
South Asia	6	7	5	4	0
Sub-Saharan Africa	40	44	28	19	9
Income Groups					
LIC & LMIC	63	59	40	28	13
Upper middle income	41	34	29	19	8
High income	48	29	23	19	6

Notes: The table shows the persistence of breaks in the growth of the tax-to-GDP ratio. Persistence of an acceleration (deceleration) episode is defined as a break that is not followed by a deceleration (acceleration) episode within 10 or 15 years. An acceleration (deceleration) episode would however be persistent if it is followed by another acceleration (deceleration) within 10 or 15 years. break is considered persistent if it is followed by another Incomplete spells are those that occur within 15 years of the end of the sample. Countries have been categorized by region and income groups. The development categories are based on the World Bank's income classification. Income categories low income and low middle income have been combined.

Table 2.5. Predictors of breaks

Panel A: Outcome is beginning of acceleration event	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Polity V	0.209									0.257
	(0.058)***									(0.077)***
1(Violence ends)		0.106								0.333
		(0.188)								(0.221)
1(Violence begins)		-0.053								-0.142
		(0.198)								(0.213)
Foreign assets and liabilities (% of GDP)			-1.356							-1.213
			(0.695)*							(1.011)
Inward and outward FDI (% of GDP)				-1.090						-0.699
				(0.447)**						(0.636)
Imports and exports (% of GDP)					0.016					0.016
					(0.010)					(0.018)
Inflation rate						-0.000				-0.000
						(0.000)				(0.000)
Government debt (% of GDP)							0.001			0.012
							(0.001)			(0.009)
1(GDP cycles: Bad times)								0.115		-0.036
								(0.076)		(0.121)
1(GDP cycles: Good times)								0.064		0.005
								(0.078)		(0.107)
1(VAT implemented)									0.098	0.459
									(0.194)	(0.231)**
Observations	4,455	4,620	3,930	3,878	4,502	4,250	4,074	4,777	4,946	2,416
Countries	138	149	148	148	148	145	146	145	152	118
Year FE	X	X	X	X	X	X	X	X	X	X

Table 2.5: Predictors of breaks (cont.)

Panel B: Outcome is beginning of deceleration event	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Polity V	-0.032									-0.091
	(0.049)									(0.062)
1(Violence ends)		-0.044								0.031
		(0.183)								(0.266)
1(Violence begins)		0.078								-0.021
		(0.156)								(0.235)
Foreign assets and liabilities (% of GDP)			-0.218							0.502
			(0.574)							(0.930)
Inward and outward FDI (% of GDP)				-0.168						-0.274
				(0.383)						(0.649)
Imports and exports (% of GDP)					-0.019					-0.029
					(0.010)*					(0.017)*
Inflation rate						-0.000				0.000
						(0.000)				(0.000)
Government debt (% of GDP)							-0.002			-0.014
							(0.003)			(0.008)*
1(GDP cycles: Bad times)								-0.047		-0.031
								(0.067)		(0.086)
1(GDP cycles: Good times)								0.115		0.066
								(0.065)*		(0.084)
1(VAT implemented)									-0.117	-0.102
									(0.197)	(0.234)
Observations	4,370	4,554	3,868	3,818	4,478	4,283	3,991	4,695	4,879	2,382
Countries	138	149	148	148	149	146	146	145	152	117
Year FE	X	X	X	X	X	X	X	X	X	X

Notes: This table presents the results from bi-variate and multi-variate probit estimations for the onset of an acceleration event (Panel A) and the onset of a deceleration event (Panel B). For more details, see Section 2.5.

Table 2.6. Sensitivity of Predictors of Breaks

Outcome:	Large accelerations	Persistent accelerations	10% trimming accelerations	Large decelerations	Persistent decelerations	10% trimming decelerations	Ordered turning points
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Polity V	0.270	0.177	0.210	-0.126	-0.067	-0.165	0.213
	(0.079)***	(0.100)*	(0.072)***	(0.069)*	(0.060)	(0.060)***	(0.067)***
1(Violence ends)	0.364	0.114	0.271	-0.090	0.000	-0.064	0.044
	(0.224)	(0.435)	(0.193)	(0.288)	(0.307)	(0.224)	(0.245)
1(Violence begins)	-0.126	-0.149	-0.051	-0.192	0.160	-0.194	0.098
	(0.217)	(0.509)	(0.187)	(0.320)	(0.254)	(0.238)	(0.187)
Inflation rate (%)	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Government debt (% of GDP)	0.012	-0.002	0.000	-0.014	-0.018	-0.018	0.015
	(0.010)	(0.013)	(0.008)	(0.008)*	(0.009)*	(0.007)**	(0.006)**
1(GDP cycles: Bad times)	-0.065	-0.053	-0.002	-0.063	0.088	0.039	0.043
	(0.124)	(0.159)	(0.092)	(0.103)	(0.109)	(0.090)	(0.089)
1GDP cycles: Good times	-0.002	-0.063	0.110	0.105	0.109	0.099	-0.037
	(0.107)	(0.139)	(0.089)	(0.097)	(0.108)	(0.090)	(0.074)
Foreign assets and liabilities (% of GDP)	-0.683	-1.371	-2.569	0.012	0.561	-0.727	-0.433
	(1.015)	(1.046)	(0.955)***	(1.042)	(1.086)	(0.829)	(0.751)
Inward and outward FDI (% of GDP)	-0.812	-0.458	-0.198	-0.327	-0.307	0.420	-0.594
	(0.682)	(0.840)	(0.633)	(0.783)	(0.715)	(0.614)	(0.514)
Imports and exports (% of GDP)	0.015	0.018	0.016	-0.043	-0.019	-0.022	0.022
	(0.018)	(0.021)	(0.015)	(0.021)**	(0.019)	(0.016)	(0.013)*
1(VAT implemented)	0.380	0.615	0.192	-0.036	-0.078	-0.030	0.291
	(0.238)	(0.254)**	(0.228)	(0.259)	(0.228)	(0.208)	(0.223)
Observations	2,443	1,705	2,295	2,459	1,908	2,112	2,045
Countries	118	108	117	117	109	117	117
Year FE	X	X	X	X	X	X	X

Notes: This table explores the robustness of the multi-variate probit results to changes in the measure of turning points. For more details, see Section 2.5.3.

2.9 Additional Tables

Table 2.A.1. Robustness: Tax to GDP growth breaks by decade and income classification (using larger growth filters)

		Average growth in T/Y		Number of breaks (by decade)				
	Breaks	pre-break	post-break	1970-1980	1980-1990	1990-2000	2000-2010	2010-2018
				Panel A: Accelerations				
Region								
East Asia & Pacific	12	-1.5	10.8	1	4	2	3	2
Europe & Central Asia	18	0.2	2.8	5	1	2	4	6
Latin America & Caribbean	21	-1.5	15.6	5	9	5	2	0
Middle East & North Africa	14	-3.0	11.0	3	3	2	5	1
North America	0	-	-	0	0	0	0	0
South Asia	6	-0.4	4.9	0	3	0	2	1
Sub-Saharan Africa	35	-2.0	13.4	4	9	11	10	1
Income Groups								
LIC & LMIC	51	-2.0	13.4	6	17	11	13	4
Upper middle income	26	-0.8	11.8	4	5	6	7	4
High income	29	-1.3	6.3	8	7	5	6	3
				Panel B: Decelerations				
Region								
East Asia & Pacific	8	4.0	-0.9	2	1	2	2	1
Europe & Central Asia	10	2.6	-0.1	0	3	2	4	1
Latin America & Caribbean	19	4.3	-3.3	6	5	4	3	1
Middle East & North Africa	9	14.1	-4.8	2	3	2	2	0
North America	1	0.5	-1.4	0	0	1	0	0
South Asia	4	1.4	-2.1	2	0	2	0	0
Sub-Saharan Africa	39	11.4	-4.3	12	12	7	4	4
Income Groups								
LIC & LMIC	46	10.0	-3.8	15	12	10	5	4
Upper middle income	27	3.9	-2.7	7	6	4	7	3
High income	17	9.0	-2.3	2	6	6	3	0

Notes: The table shows the total number of breaks in the growth of the tax-to-GDP ratio and the average growth in tax-to-GDP ratio before and after the break for acceleration and deceleration episodes. We estimate the 8-year average before and after break. Countries have been categorized by region and income groups. The development categories are based on the World Bank's income classification. Income categories low income and low middle income have been combined.

Table 2.A.2. Tax to GDP growth breaks by decade and income classification (using a smaller 5 year inter-break period)

		Average growth in T/Y		Number of breaks (by decade)				
	Breaks	pre-break	post-break	1970-1980	1980-1990	1990-2000	2000-2010	2010-2018
				Panel A: Accelerations				
Region								
East Asia & Pacific	21	-0.4	7.6	1	7	4	6	3
Europe & Central Asia	27	0.2	2.5	5	4	6	6	6
Latin America & Caribbean	38	-1.3	12.7	7	14	11	6	0
Middle East & North Africa	18	-3.7	11.8	3	6	3	5	1
North America	0	-	-	0	0	0	0	0
South Asia	7	-0.5	4.7	0	3	1	2	1
Sub-Saharan Africa	60	-2.0	14.8	5	15	15	24	1
Income Groups								
LIC & LMIC	83	-1.8	14.4	8	24	19	28	4
Upper middle income	43	-1.3	10.2	5	12	11	11	4
High income	45	-0.9	4.9	8	13	10	10	4
				Panel B: Decelerations				
Region								
East Asia & Pacific	19	6.0	-0.1	2	3	6	5	3
Europe & Central Asia	22	2.5	-0.3	2	5	5	8	2
Latin America & Caribbean	37	9.1	-1.5	6	12	10	7	2
Middle East & North Africa	17	12.4	-3.7	2	4	6	4	1
North America	3	1.2	-0.6	1	0	1	1	0
South Asia	8	2.1	-1.6	2	1	5	0	0
Sub-Saharan Africa	63	9.5	-3.4	14	19	14	9	7
Income Groups								
LIC & LMIC	84	9.2	-2.5	17	22	24	12	9
Upper middle income	49	7.4	-1.3	7	11	13	15	3
High income	36	5.9	-2.3	5	11	10	7	3

Notes: The table shows the total number of breaks in the growth of the tax-to-GDP ratio and the average growth in tax-to-GDP ratio before and after the break for acceleration and deceleration episodes. We estimate the 8-year average before and after break. Countries have been categorized by region and income groups. The development categories are based on the World Bank's income classification. Income categories low income and low middle income have been combined.

Table 2.A.3. Discrete (large) events for all RHS vars

Outcome:	Acceleration (1)	Deceleration (2)
1(Polity V: $\triangle \gg 0$)	0.653	-0.257
	(0.152)***	(0.205)
1(Polity V: $\triangle \ll 0$)	0.094	0.189
	(0.250)	(0.220)
1(Violence ends)	0.528	-0.062
	(0.204)***	(0.245)
1(Violence begins)	-0.302	-0.021
	(0.206)	(0.200)
1(Inflation: $\triangle \gg 0$)	0.107	-0.019
	(0.128)	(0.105)
1(Inflation: $\triangle \ll 0$)	0.024	0.352
	(0.122)	(0.111)***
1(Debt: $\triangle \gg 0$)	0.233	-0.000
	(0.123)*	(0.133)
1(Debt: $\triangle \ll 0$)	-0.206	0.210
	(0.141)	(0.117)*
1(GDP growth: $\triangle \gg 0$)	0.179	0.076
	(0.151)	(0.132)
1(GDP growth: $\triangle \ll 0$)	-0.026	0.124
	(0.128)	(0.135)
1(Capital openness: $\triangle \gg 0$)	0.103	0.197
	(0.157)	(0.130)
1(Capital opennes: $\triangle \ll 0$)	-0.020	-0.154
	(0.125)	(0.143)
1(FDI openness: $\triangle \gg 0$)	-0.161	0.079
	(0.147)	(0.126)
1(FDI opennes: $\triangle \ll 0$)	0.102	0.002
	(0.139)	(0.117)
1(Trade openness: $\triangle \gg 0$)	0.170	-0.189
	(0.133)	(0.131)
1(Trade opennes: $\triangle \ll 0$)	0.098	0.058
	(0.133)	(0.105)
1(Vat implemented)	0.425	-0.143
	(0.230)*	(0.220)
Observations	2,789	2,778
Countries	121	122
Year FE	X	X

Notes: This table estimates multivariate probit regressions, where the outcome is the onset of an acceleration (column 1) and the onset of a deceleration (column 2). The explanatory variables are described in Section 2.5.3.

Table 2.A.4. Robustness of polity results

Outcome:	Acceleration	Deceleration	Acceleration		Deceleration		Acceleration	Deceleration	Acceleration	Deceleration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Polity V	0.216	-0.058								
	(0.072)***	(0.059)								
Executive recruitment			0.479		-0.044					
			(0.200)**		(0.138)					
Political competition				0.276		-0.164				
				(0.127)**		(0.126)				
1(Polity V: $\triangle \gg 0$)							0.553	0.027		
							(0.121)***	(0.167)		
1(Polity V: $\triangle \ll 0$)							0.061	0.026		
							(0.179)	(0.180)		
1(Transition to democracy)									0.801	0.135
									(0.153)***	(0.206)
1(Transition to autocracy)									0.019	0.081
Modification to main specification	Include country FE		Decompose Polity V into exec. and pol. comp.				Focus on large Polity V changes		Focus on transitions autoc. $\Leftrightarrow$ democ.	
Observations	4,200	4,139	4,200	4,200	4,139	4,139	4,476	4,390	4,486	4,400
Countries	80	85	138	138	138	138	139	139	139	139
Year FE	X	X	X	X	X	X	X	X	X	X
Country FE	X	X								

Notes: This table investigates the robustness of the Polity V result to differences in specification and measures of explanatory variables. The different columns modify the main specification from Table 2.5 in ways that are described in the top row of the bottom panel. For more details, see Section 2.5.4.

Chapter 3

Ecological Benefits of Place-Based Policies: Evidence from Protected Areas in India

3.1 Introduction

Do place-based environmental policies support forest conservation? If so, do these come at a cost to economic development in these locations? Governments worldwide are increasingly employing place-based conservation efforts as a prominent strategy for forest conservation. These policies concentrate on specific geographic areas, aiming to address the unique ecological conservation challenges and opportunities they present. In 2020, over 16% of the total global land mass (excluding Antarctica) had been designated as official protected and conservation areas.[1] Yet, relatively little is known about the environmental impacts of these place-based measures. In this paper we explore the ecological and economic impact of such protected areas in the context of India, one of the 36 countries where forest cover has increased over the past few decades (Potapov et al. (2022)).

Restoring and protecting forest cover plays a crucial role in climate mitigation and adaptation (IPCC (2022)). The IPCC report highlights the need to protect at least 30%

[1]The network of protected areas has expanded over time, with countries committing to increase protected area coverage as part of international conservation agreements like the Convention on Biological Diversity (CBD) and the Sustainable Development Goals (SDGs). Since 2010, an additional 21 million sqkm has been placed within protected and conserved areas (UNEP-WCMC and IUCN (2021)).

of land and sea, stating that "30% or even 50% of land and sea needs to be protected or restored to confer adequate protection for species and ecosystem services." A vast majority of economic literature has predominantly focused on market-based environmental policies, in contrast to place-based command-and-control style policies for environmental conservation (Whitehead and Stavins (1997), Stavins (2003), Schelling (1992), Greenstone, Kopits, and Wolverton (2013)).[2] However, these place-based environmental policies are ubiquitous (and growing), and given the diverse nature of environmental problems, it is impractical to envision market-based solutions alone to be sufficient (Swaney (1992)). In light of these considerations, this paper aims to explore the role of place-based policies in conservation of forest cover.

In this study, we examine the potential of achieving ecological gains in parallel to economic growth. While traditional conservation efforts have primarily focused on ecological outcomes, there is increasing recognition of the need to achieve both ecological and economic benefits simultaneously – to balance economic growth, job creation, poverty reduction, and the preservation of natural resources and ecosystems. The economic literature has also highlighted trade-off between economic development objectives and environmental goals (Arrow et al. (1995), Alix-Garcia et al. (2013), Asher, Garg, and Novosad (2020)).

Existing (ecological) literature portrays a somewhat negative picture of protected areas. This can arise because protected areas need not be well enforced, and are typically established in regions with high ecological value but limited economic opportunities. Consequently, protected areas often have high poverty levels. The regulations accompanying protected areas also often involve land-use restrictions that are claimed to lead to job losses, social differentiation, inequality, and uncertainty over property rights (Fortin and Gagnon (1999), Pfeffer, Schelhas, and Day (2001); List, Margolis, and Osgood (2006);

[2] Command and control policies involve strict regulations and government enforcement, while market-based policies rely on market mechanisms such as emissions trading and pollution pricing to incentivize environmental conservation.

Robalino (2007)). Consequently, numerous studies report negative correlations between nature conservation and local economic development across countries (Ferraro (2002); Cernea and Schmidt-Soltau (2006)). But protected areas might also generate new income by attracting tourism, or by inducing infrastructure development. A few studies have shown that protected areas do improve livelihoods, and enhance overall well-being (Andam et al. (2010), Mullan et al. (2009), Balmford et al. (2002), Sims (2010); Canavire-Bacarreza and Hanauer (2013); Naughton-Treves, Holland, and Brandon (2005), Naidoo et al. (2019))). The relationship between protected area assignment status, remoteness of areas, and their impact on economic development remains tricky to study as the placement of forest conservation interventions is typically non-random.

In this paper, we overlay village-level demographic, economic, and forest cover data with protected areas for India. Using data for roughly 375 protected areas established before 1995 and a regression discontinuity design, we find that protected areas help with forest cover restoration while simultaneously supporting improvement in economic activity. Villages inside protected areas had 37% higher forest cover in the year 2000 compared to their village counterparts on the other side of the protected area boundary. Villages on both sides of the protected area boundaries experienced an increase in forest cover during 2000 and 2014, but we find that villages inside protected areas experienced a 4% higher increase in forest cover during this time period. This result speaks directly to the effectiveness of protected areas – not only do protected areas help conserve existing forest cover, but they also help grow forest cover as well.

We find that this increase in forest cover does not come at a cost to economic outcomes. Villages inside protected areas had three-quarters the economic activity in 2000 (as measured by nightlights) compared to villages right outside protected areas. This result corresponds to the *correlational* concerns flagged in the existing literature discussed above. However, we find that villages inside protected areas experienced a 17% larger increase in nightlights between 2000 and 2013 compared to the villages on the other side of the protected area boundary. There are very small differences in employment and consumption among these villages on average.

We also separately study village subsamples in sanctuaries and national parks. We find that wildlife sanctuaries have been particularly successful at achieving ecological gains in forest cover with simultaneous improvement in economic outcomes during this time period. This is driven in part by an increase in employment in tourism in these locations. We also provide some descriptive correlations for states with different shares of spending in forestry sector. We find that states among the top tercile of spending share on forestry, experience larger conservation of forest cover with significantly larger improvements in employment as well. By examining the role of state financial support in the establishment and maintenance of protected areas, we seek to contribute to the ongoing discourse on effective and sustainable environmental governance.

The rest of the paper is organized as follows. In Section 3.2, we discuss the institutional context of protected areas in India. In Sections 3.3 and 3.4, we define our data and methodology. In Section 3.5, we present our results, validation, and heterogeneity tests. Section 3.6 concludes.

3.2 Background

Protected areas play a vital role in the global conservation of biodiversity and natural resources. They are designated spaces managed and regulated by governments or relevant authorities to protect ecosystems, habitats, and species. These areas serve as havens for wildlife, support ecological processes, and provide opportunities for scientific research, education, and recreation.

In India, protected areas have been the primary strategy employed to conserve biodiversity and wildlife. The Indian government enacted the Wildlife Protection Act (WPA) in 1972, driven by concerns over widespread deforestation and the subsequent decline in biodiversity. The WPA defined four types of protected areas: National Parks, Wildlife Sanctuaries, Community Reserves, and Conservation Reserves. These areas were typically established within existing Reserve Forests, as determined by state governments. The state government can fix and alter the boundaries with prior consultation and approval with the National Board of Wildlife.

Protected areas are administered by the wildlife wing of the state forest departments, while other recorded forest areas are administered by the territorial wings. Each area is governed by a 10-year working plan, which acts as the blueprint for balancing the objectives of conservation and human welfare at the local level. The plans are prepared by forest department officers.

Currently, India has 869 established protected areas comprising of 104 National Parks, 551 Wildlife Sanctuaries, and 127 Community Reserves have been established. Growth of Protected Areas over time is plotted in Figure 3.1. A large number of protected areas (roughly 50% of the total protected areas and 68% of total land under Protected Areas) were established in the 1970s and 1980s. However, the effectiveness of protected areas varies, and challenges persist, including governance issues, funding limitations, illegal activities, and conflicts with local communities.

3.3 Data

We combine four different data sources to estimate the ecological and economic impacts of protected areas. We digitize protected area maps from ENVIS Centre on Wildlife Protected Areas India to determine the boundaries of PAs. We overlay these maps on geo-referenced village datasets and validate the overlap using villa-level lists of each individual protected area. The core ecological outcomes are constructed using high-resolution satellite-based measure of forest cover. For village-level demographic and economic outcomes, we use the 1991, 2001 and 2011 Population Censuses and 3rd through

6th rounds of the Economic Census from Asher, Lunt, et al. (2021). These are census datasets that describe the entire population of India and are geocoded to the village, town, and subdistrict levels. Finally, we collect sector-level expenditures and share of state gross domestic products which we use as proxy-measures of state implementation efforts.

Protected areas

We digitized each protected area map from ENVIS maps made available by Wildlife Institute of India, Dehradun sponsored by the India Ministry of Environment, Forests & Climate Change. Where geo-references like latitude and longitudes were not provided on the maps, we obtained PA boundaries from the Protected Planet which is the online interface for the World Database on Protected Areas (WDPA), a joint project of IUCN and UNEP, and the most comprehensive global database on terrestrial and marine protected areas. Year of establishment of these protected areas was collected from ENVIS. These digitized maps were then verified against lists of villages classified under each protected area which were available from various state-level forestry department websites. We focus on protected areas established on terrestrial mainland, had overlap with village-level data, and excluded most small PAs less than 5sqkm. This gave us a sample of 490 protected areas across 29 Indian states.

Village-level data

We use the 1991, 2001 and 2011 population censuses of villages compiled by Asher, Lunt, et al. (2021). The population censuses provide village characteristics, demographic information, village and town public goods, village amenities and household characteristics. The Economic Censuses are complete enumerations of all non-farm establishments undertaken in 1990, 1998, 2005 and 2013, including informal and non-manufacturing firms. The Economic Census reports total employment and industry for all firms. We create variables estimating share of total employment, as well as employment in key sectors of interest, specifically, employment share in forestry as well as employment in the hospitality sectors which include tourism, hotels, and restaurants. The industry categorization for the 2005 Economic Census places logging firms in the same industry category as firms engaged in the conservation of forest plantations, management of forest tree nurseries and other afforestation categories. We, therefore, focus on the years 1990, 1998, as well as 2013 in our analysis. In addition, we use the imputed village-level consumption measures as well. This household microdata comes from the Socioeconomic and Caste Census (SECC) of 2012, which describes every household and individuals in India. The imputation methodology is discussed in Asher, Lunt, et al. (2021). Finally, distance of a village from the Protected Area boundary is measured using straight-line shortest distance of a village-centroid to the closest protected area boundary. PAs are not restricted to administrative village boundaries so villages can be both inside and outside a protected area. We thus estimate share of a village land area that is inside a protected area.

Forest Cover

We use the Vegetation Continuous Fields (VCF) standardized publicly-available satellite-based dataset for our analysis. This dataset is available at 250m resolution and provides annual tree and non-tree vegetation cover from 2000-2014 in the form of the percentage of each pixel under forest cover Townshend et al. (2011). The VCF measure is a prediction of the percentage of a pixel that is covered by forest and other non-tree vegetation, generated from a machine learning model based on a combination of images from MODIS and samples from higher-resolution satellites. We prefer VCF to finer granular data from the Global Forest Cover (GFC) dataset which describes baseline forest cover in the year 2000 and a binary indicator for the year of deforestation for each 30mx30m pixel. This is because India is documented to have increased forest cover in the last few decades and the GFC focuses only on deforestation. We are specifically interested in impact on conservation efforts so prefer the VCF for our analysis.

For our village-level estimation of forest cover, we follow the methodology adopted by Asher, Garg, and Novosad (2020) to estimate total and average forest cover at the village-level.

Nightlights

We use nightlights as a proxy for economic activity (see Henderson, Storeygard, and Weil (2011)). We use MSP-OLS annual measures of nighttime luminosity, measured at 30-arc-second grids. We use stable lights which take into account lights from cities, forest fires, cloud cover and more. This data is available from 1994 to 2013. For village-level analysis, we aggregate the pixel-level data to village-level following the approach in Asher, Lunt, et al. (2021).

State-level financial data

The Indian Central government holds the power to make forest policy, but the state governments and state-level forestry departments are vested the responsibility for implementing it. We use two sets of datasets to capture variation in state-level importance of forestry and conservation. First, we use sector-level estimates of gross value added at the state-level from 1960-1 onwards. This comes from the World Bank data set, A Database on Poverty and Growth in India, prepared by Özler, Datt, and Ravallion (1996) as part of the research project on 'Poverty in India 1950-1990'. We use the net state domestic product in forestry and logging as a share of total (all sector) net state domestic product.

Next, we digitize state-level revenue and expenditure accounts from 1950 onwards from the Combined Finance and Revenue Accounts of the Union and State Governments prepared by the Comptroller and Auditor General of India. We estimate the share of total expenditure on forestry using government expenditure on forestry which falls under two main heads: conservation efforts and establishments. We also collect information on revenue from forests but these revenues can come from produce of government forests as well as revenue from forests not managed by the government.

For both datasets, we rank states in percentiles based on the state average for the entire study period.

3.4 Research Design

The impacts of place-based conservation policies, in this case, the establishment of Protected Areas, are often challenging to measure. Protected areas are established taking into account biodiversity and economic potential making a simple difference in averages inside and outside protected areas insufficient to estimate impacts. We address this by combining geo-referenced village and pixel-level data with a regression discontinuity design (RDD). By overlaying protected area maps with village maps provides us with village-level treatment designation. Villages inside these protected areas are *treated*, while villages on the other side, are *exempt*. The PA boundaries are enforced at the national level,[3] and in theory, enforcement should change discretely at the boundary of the subjected region. As long as these protected area boundaries were even just slightly obeyed, the likelihood of *treatment* changes discontinuously at these boundaries, allowing us to use a fuzzy RDD.

We follow the following RDD specification with the shortest distance of village centroids to the PA boundary, $Dis_{v,d}$, as the running variable.

$$y_{v,d,t} = \alpha_0 + \alpha_1 1[Dis_{v,d} < 0] + \alpha_2 Dis_{v,d} * 1[Dis_{v,d} < 0] + \theta PA_d + \delta X_{v,d,t} + \epsilon_{v,d,t} \tag{3.1}$$

where $y_{v,d,t}$ is the outcome of interest in village v close to designated protected area d at time t. The distance at the PA boundary is normalized to zero. Villages inside the protected areas are coded as negative distance to the boundary, $Dis_{v,d} \leq 0$. $X_{v,d,t}$ is a vector of village-covariates that includes demographics and village area. We also control for protected area fixed effects. These village controls and PA fixed effects are not necessary for identification but improve the efficiency of the estimation. The choice of the bandwidth

[3]In 1966, India established the Indian Forestry Services as one of the 3 all-India services together with the Indian Administrative and Indian Police Services. Indian Forest Officers are tasked with the management and conservation of Protected Areas within their assigned state

can play an important role in the RD estimates. The optimal bandwidth as proposed by Calonico, Cattaneo, and Titiunik (2015) varies by choice of outcome ranging from about 4500 meters to 6000 meters. We test the sensitivity of the RD estimates of each of our main outcome variables to various bandwidths within this range and choose 5000 meters for our preferred specification to ensure consistency across outcomes in our analysis. We use a triangular kernel to give higher weights to points nearer to the discontinuity threshold (Imbens and Lemieux (2008)). We cluster the standard errors at the protected area cluster level.

These regression discontinuity estimates can be interpreted as causal estimates of the effect of being in a designated PA if village covariates vary smoothly at the PA boundary threshold. This assumption is needed to ensure villages located just outside the PA catchment are an appropriate counterfactual for those located just inside it. The related other assumption requires no sorting of individuals based on PA boundary. Table 3.1 presents the mean values of village characteristics including demographic variables such as population density, population growth, literate share of the population as well as physical characteristics like distance to river bodies and altitude. While there are average differences between villages inside and outside protected areas but we find no significant differences in these baseline covariates using the RD estimation. In Figure 3.3, we plot the mean of these variables in 200 meters distance bins. Left of the 0km threshold are villages inside the protected areas. Baseline village characteristics are thus continuous at the treatment threshold. Under the assumption of continuity of all other village characteristics other than treatment status, the fuzzy RD estimator calculates the local average treatment effect (LATE) of assignment inside a protected area.

In Section 3.5, we first estimate the impact of these protected areas on ecological and economic outcomes at the village level. However, protected areas in our context do not follow village boundaries. This implies that a given village can be both *inside* as well as *outside* the protected area. To deal with this, in our main specification, we code a village as *inside* if at least 70% of its land mass lies within a protected area. We test sensitivity using other thresholds like 50% and 100%. Next, we exploit the pixel-level forest cover and nightlights data to move away from village-level estimation. For this, we estimate the distance of each pixel from the protected area boundary and use a similar RDD specification but at the pixel-level (instead of the village level v).

Finally, we run our estimates on a number of subsamples to test if our estimates are driven by certain characteristics of protected areas or their geographical location:

- Year of establishment of PA: we exploit the temporal variation in the establishment of PAs (as shown in 3.1). For our main specification, we use villages within 5000m of PAs established prior to 1995 given our outcome variables are post that time period. We also run our empirical strategy on villages around PAs established in the 2010-2018 time period to explore how villages would have performed on conservation efforts without the protected areas. This approach assumes that the criteria for the establishment and maintenance of the older vs the newer PAs are similar.

- Size of PA: we run our estimation on villages in the top 50 percentile of the size distribution to test how size of PAs drive our estimation results.

- Type of PA: Protected areas in India comprise of national parks, wildlife sanctuaries, and conservation and community reserves. While most of the provisions are common for sanctuaries and national parks, there are some key differences that have implications for our study of ecological and economic outcomes. For instance, livestock grazing is prohibited in a national park, but can be allowed in a regulated manner in sanctuaries. Thus, we study both tree and non-tree vegetation canopy using the VCF MODIS dataset. In addition, boundaries of sanctuaries are not well defined and controlled biotic interference is permitted, while the boundaries of a national park are well defined and no biotic interference is permitted (Dar, Dar, and Nabi (2022)).

- Geographical location of PA: State governments in India exercise administrative control over all statutorily recognized forests and other government-owned lands in the country (with some restrictions). The State Forest Department is vested with the task of administration and management of PAs. This implies that the implementation and maintenance of PAs could vary by states. We use state-level variation in the importance of forestry as sector for the state GDP as well as share of total state expenditure that is spent on forestry sector to explore state-level variation in the impact of place-based policies. We divide states in terciles for each category to explore how much of the total effects are driven by a few states.

3.5 Results

We document three key findings in this paper. First, across both village as well as pixel-level analysis, we find that protected areas support forest conservation. This impact is meaningful and statistically significant across a number of robustness checks. Second, we find that this conservation does not come at a cost to economic activity. Finally, state expenditure on forestry conservation efforts is correlated with larger increase in forest cover in these protected areas.

We begin by discussing some descriptive statistics for the villages within protected areas and those neighboring the protected area boundaries. Figure 3.2 graphically represents the raw village-level average forest cover (left panel) and night time luminosity (right panel) within 10 kilometers on either side of the Protected Area boundary. Forest cover has been rising over the time period with a blip in the year 2013 reflecting concerns with satellite-based datasets. Forest cover in villages inside protected areas (blue dashed line) is on average higher than forest cover in villages right outside (red dashed-line). Nightlights on the other hand are higher in villages outside PAs on average and there has been a growth in economic activity in this time period.

Tables 3.2 and 3.3 present the RD estimate of the impact of protected areas on each outcome. Figures 3.4, 3.5, and 3.6 present a graphical representation of these estimates for protected areas established prior to 1995. We also use a donut approach excluding villages within 2km of the protected boundary (depicted by the grey dots in the figures). This is because of a couple of reasons. First, imperfect ground implementation of protected areas. Protected areas often do not follow village administrative boundaries making enforcement even harder. This is especially the case for sanctuaries as boundaries of sanctuaries are not as well defined. Second, our digitization of protected areas maps are expected to have minor errors. We compare our digitized data to the list of villages designated PAs to minimize such errors. Below we discuss each outcome in detail.

Forest Cover:

Figure 3.4 (panel a) shows the discontinuity at the border in log forest cover in the year 2000. Forest cover in a village is estimated by summing the total forest cover in all the pixels in a village and dividing by the number of pixels. Villages inside the protected area (left of the 0 threshold) have higher forest cover. This remains true for the entire span for our forest cover dataset. RDD estimation results in Table 3.2 show that villages inside protected areas that were established prior to 1995, had 37% higher forest cover in 2000. This result could be both due to placement of these place-based protected area conservation policies in areas with higher original forest cover, or due to the conservation efforts in the past.

Change in Forest Cover:

Next, we look at change in log forest cover between 2000 and 2014. Figure 3.4 (panel b) highlights the difference in growth in forest cover at the protected area boundary. While both villages inside and outside the protected areas experience growth in forest cover in this time period, villages inside have a higher ecological improvement as measured by increase in forest cover. This difference is smaller than the difference in forest cover above – villages inside a protected area have a 4% larger increase in protected area as shown by Table 3.2. This result speaks directly to the effectiveness of protected areas that not only do protected areas help conserve existing forest cover, they help grow forest cover as well.

Nightlights:

Villages inside protected areas exhibit lower economic activity, as measured by nightlights. Figure 3.5 (panel a) shows the discontinuity at the PA boundary in log nightlight in the year 2000. This holds true for the entire sample period 1993-2013. Villages inside a protected area have 25% lower nightlights on average. This does not necessarily imply protected areas hinder economic activity because states choice of PA boundaries are expected to take into account forest cover and economic potential.

Change in Nightlights:

In order to explore the impact on economic activity we next look at the change in log nightlights between 2000 and 2013, depicted in Figure 3.5 (panel b). Overall nightlights increase for both regions inside and outside protected areas during this period. Interestingly, protected areas see larger increase (roughly 17%) in nightlights in this period. To note, the level differences in nightlights in the year 2013 remain so villages inside still have lower economic activity as opposed to their counterparts outside. However, villages inside protected areas do slowly catch-up.

Employment and Changes in Employment:

Nightlights serve as a proxy for overall economic activity, so we explore employment and employment growth differences across the PA boundary. There is no difference in employment share in the formal sector in 1990 or even 23 years later. Growth in total employment share is also negligible. We explore differences in share of formal sector employment in forestry & logging. As shown in Table 3.3, there are very little differences in employment in forestry at the PA boundary threshold. Next, we explore differences in the hospitality sector which comprises of employment in tourism, restaurants, and hotels.

Villages inside protected areas start with (statistically insignificant) lower employment share in hospitality, but growth in employment in hospitality is larger inside protected areas.

Consumption:

We find no discernible difference in log (imputed) consumption in 2011 at the PA boundary, as depicted by Table 3.3. This hints that these place-based policy measures help forest conservation without significant economic impacts on livelihoods.

3.5.1 Validity checks

We run our RD specification using different bandwidths polynomial specifications, and weights. We also remove village controls and protected area fixed effects. The results are robust to these choices. Next, we check for robustness using different classification of boundary villages inside/outside protected areas. In our main specification, we use villages that are at least 70% inside PA boundary. We check robustness of results with definitions like 50% and 100%. Results are slightly muted if we use the choice of 50% (as shown in Tables 3.4 and 3.5 suggesting the dilution of fuzziness of the boundary.

Next, we use our pixel-level data on forest cover and nightlights using the same RD specification above. Figures 3.A.1 (panel e) shows a sharp increase in forest cover inside the PA boundary. Table 3.A.1 highlights the RD results of forest cover and growth over the same time period using pixel-level data. Pixels just inside protected area boundaries have a 9% higher log forest cover in the year 2000. Increase in forest cover is also higher inside protected areas, pixels inside experiencing a 2% larger increase over the 14-year period until 2014. These estimates while slightly smaller than the village-level analysis are the same order of magnitude and highlight the conservation impacts of protected areas.

We use the nightlight pixel-level data and find no discernible differences at the PA boundary. This is partly driven by two reasons - nightlight grids are four times larger than

VCF MODIS and nightlights in these regions are so low that differences at pixel level are hard to observe.

Finally, we also check validity of our RD specification using data on newly formed protected areas. A concern with the above result on conservation inside protected areas is that regions inside protected areas would have fared well on conservation even without any government interventions. We run our estimation on villages in and around protected areas established between 2010-2018. This leaves us with a sample of 29 protected areas. Table 3.A.2 presents results for forest cover and nightlight differences at the PA boundaries of these newly formed PAs. We find that villages that fall within PA boundaries started with higher forest cover even before establishment of protected areas. This suggests that these protected areas are well-placed in areas with higher forest cover. However, the change in forest cover without the establishment of PA was no different from villages right outside the pseudo PA boundary. Assuming there is no difference in the establishment and maintenance of the old PAs discussed in section 3.5 and these new PAs, this result suggests that protected areas support conservation efforts above and beyond overall state-level improvements.

3.5.2 Heterogeneity analysis

As discussed in section 3.4, we run our RD specification on subsamples of data, including size of the protected areas. Protected areas vary substantially in size - the median protected area in our sample covers a land area of 111 sqkm, the mean is 302sqkm. To alleviate the concern that the results are driven by the larger subset of villages, we run the estimation on villages in the top 10 and top 50 percentile of the size distribution. Our estimates are not driven by the largest protected areas in the top 10 percentile. Villages in protected areas in top 50 percentile of the size distribution constitute roughly 70% of our study sample and most of these estimates on forest cover, conservation, and economic activity are driven by this group as evident in Tables 3.4, 3.5. Villages in larger protected areas do better not just on forest cover and conservation, but also employment and consumption matters as highlighted in Table 3.6. There is, however, no discernible significant difference in change in employment in these larger protected areas.

3.5.3 Further analyses

To complete this section, we provide two additional investigations of the results.

Type of PA:

So far we have pooled all protected areas like national parks, wildlife sanctuaries, as well as conservation and community reserves in our analysis. As discussed in section 3.4, there are some key differences between sanctuaries and national parks that have implications for our study of ecological and economic outcomes. Livestock grazing is prohibited in a national park, but can be allowed in a regulated manner in sanctuaries. We thus, separately run our analysis on subsamples of villages in and around sanctuaries and national parks. This is a tricky exercise as often there are wildlife sanctuaries next to national parks. National Parks have a higher mean forest cover both inside and outside protected areas, however, the difference in forest cover created around a PA boundary is more stark closer to wildlife sanctuaries. Villages inside sanctuaries have 38% higher forest cover compared to their village counterparts just outside. The growth in forest cover around sanctuaries is also larger.

Sanctuaries also differ from National Parks in the average level and growth of nightlights inside the protected area boundary. Areas with sanctuaries experience higher nightlights overall, however, the differences in log nightlights in year 2000 at the PA boundary for villages inside and just outside protected areas are even more stark. Villages just inside the discontinuity threshold at wildlife sanctuaries experience 30% less nightlights compared to those right outside. We also find the growth in nightlights is larger for villages inside wildlife sanctuaries rather than outside – wildlife sanctuaries help increase economic activity. The nightlight discontinuity in levels, as well as their growth at national parks, is less stark.

We also study differences in employment and consumption patterns separately at wildlife sanctuaries. While there are no differences in the share of employment and share of employment in the year 1990, there are distinct patterns in employment growth. Villages inside sanctuaries have a larger increase in growth in employment in the hospitality sector between 2013 and 1990 partly driven by tourism. These differences also manifest in consumption differences. Villages inside wildlife sanctuaries experience 4% larger consumption levels than their village counterparts outside. There are no noticeable differences for national parks.

Geographical location of PA:

The importance of state-level variation in protected areas lies in the fact that state governments in India hold administrative control over all statutorily recognized forests and other government-owned lands in the country, albeit with certain restrictions. The responsibility for the administration and management of PAs rests with the State Forest Department. This indicates that the implementation and maintenance of PAs can differ across states.

To examine the impact of place-based policies, we utilize the variation at the state level in the significance of the forestry sector for the state's GDP and the proportion of total state expenditure allocated to the forestry sector. By categorizing states into terciles based on each of these factors, we can explore the extent to which the overall effects are driven by a few states. This approach allows us to understand how state-level variations influence the outcomes and effectiveness of place-based policies in different contexts.

First, we study the gross state domestic product of forestry which reflects the economic value generated by the forestry sector within a particular state. States with a substantial economic stake in the forestry sector are more likely to derive value from logging efforts which can reduce the conservation and sustainable management of their forested areas, including protected areas. We find that villages in protected areas located in states with higher reliance on forestry experience very little improvement in conservation (as shown in Table 3.4). These places do experience increase in employment in forestry related activities. This is not to say that these protected areas are not well-implemented as without the state involvement, the conservation efforts could have been even more muted.

Next, we look at state spending on forestry as share of total expenditure. We find that protected areas in states with the largest share of total spending on forestry experience 16% higher increase in forest cover compared to regions outside (Appendix Table 3.8). These states manage these conservation outcomes while sustaining a lot of economic growth in these protected areas as well. Villages inside protected areas in the top tercile of state spending experience 49% increase in forest cover as compared to neighboring villages right outside protected areas. They also experience larger increases in growth in employment especially in the hospitality sector. In contrast, villages inside protected areas in states with the lowest relative share of spending on forestry experience no discernible change in forest cover or economic activity as compared to those right outside.

State expenditure on forestry can be utilized for activities such as habitat conservation, wildlife protection, infrastructure development, and community engagement within and around protected areas. Adequate financial resources enable states to enhance the effectiveness of their conservation efforts and ensure the long-term viability of protected areas. This economic value can translate into greater attention, resources, and investment allocated to the maintenance and management of protected areas. Furthermore, state expenditure on forestry can serve as an indicator of the state's commitment to environmental sustainability and conservation. States that allocate a higher proportion of their expenditure to the forestry sector demonstrate a greater recognition of the value of forests and their ecosystem services. Such states are more likely to adopt policies and measures that support the maintenance of protected areas, including stricter regulations, enhanced monitoring and enforcement, and investment in ecological restoration.

3.6 Conclusion

In this paper, we shed light on the ecological gains resulting from the establishment of protected areas. The findings reveal that villages located within protected areas experience not only ecological benefits but also enhanced economic activity, predominantly driven by the growth of the tourism sector, especially in wildlife sanctuaries.

Furthermore, our study highlights the important role of financial allocations in achieving successful forest conservation outcomes. States that allocate a higher share of expenditure to the forestry sector demonstrate stronger conservation outcomes, indicating the significance of sustained investment in conservation efforts.

While these are just local average treatment effects, the paper provides valuable insights into the potential of place-based policies to achieve both ecological and economic gains simultaneously. By effectively managing and promoting the establishment of protected areas, governments can contribute to forest conservation while fostering economic growth and sustainable development. We aim to estimate the economic benefits of this increase in forest cover using the approach in Jayachandran et al. (2017). However, it is essential to recognize the challenges associated with the establishment of protected areas, including potential conflicts with local communities and the need to strike a balance between conservation goals and the rights of individuals who depend on these resources.

3.7 Acknowledgements

This chapter is coauthored with Asher, Sam; Garg, Teevrat; and Novosad, Paul. The dissertation author was the primary author of this chapter.

3.8 Figures and Tables

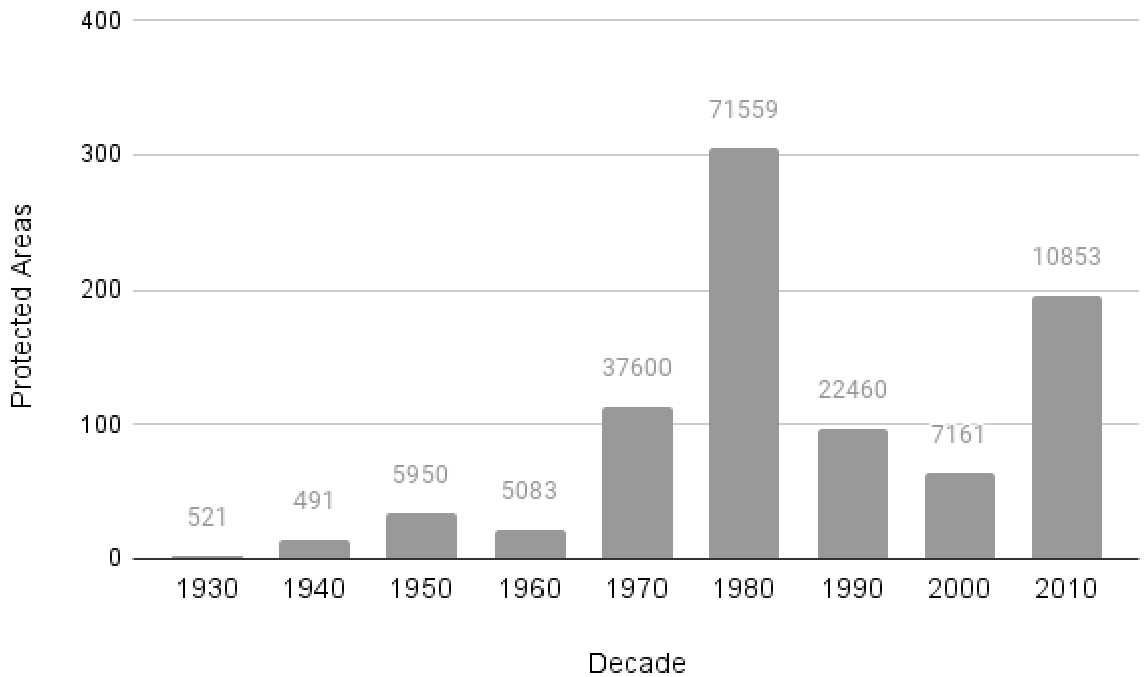


Figure 3.1. Growth of Protected Areas over time

Notes: The bar plot presents the number of protected areas established in every year. The text on the top of each bar denotes the area (in sqkm) of the total land area established as protected area in the respective decade.

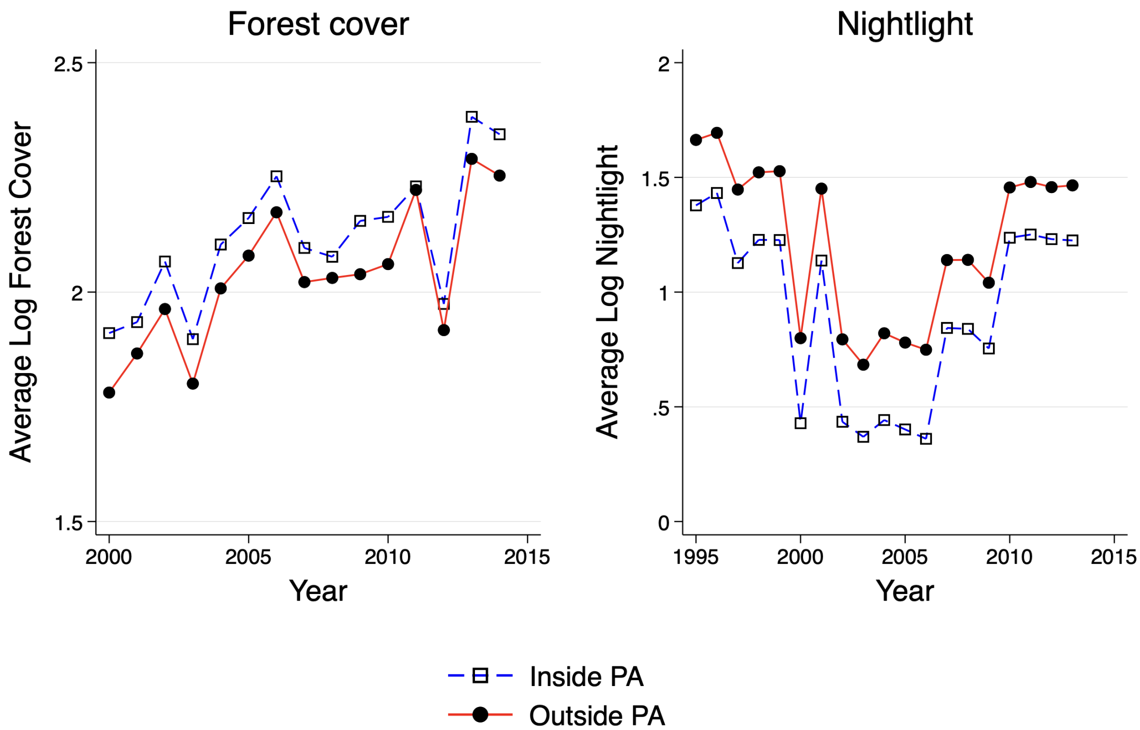


Figure 3.2. Means over time (within 10km of PA boundary)
Notes: The figure presents the mean log forest cover (panel a) and mean log nightlight (panel b) for cells that lie within 10 kilometers of the protected area boundary.

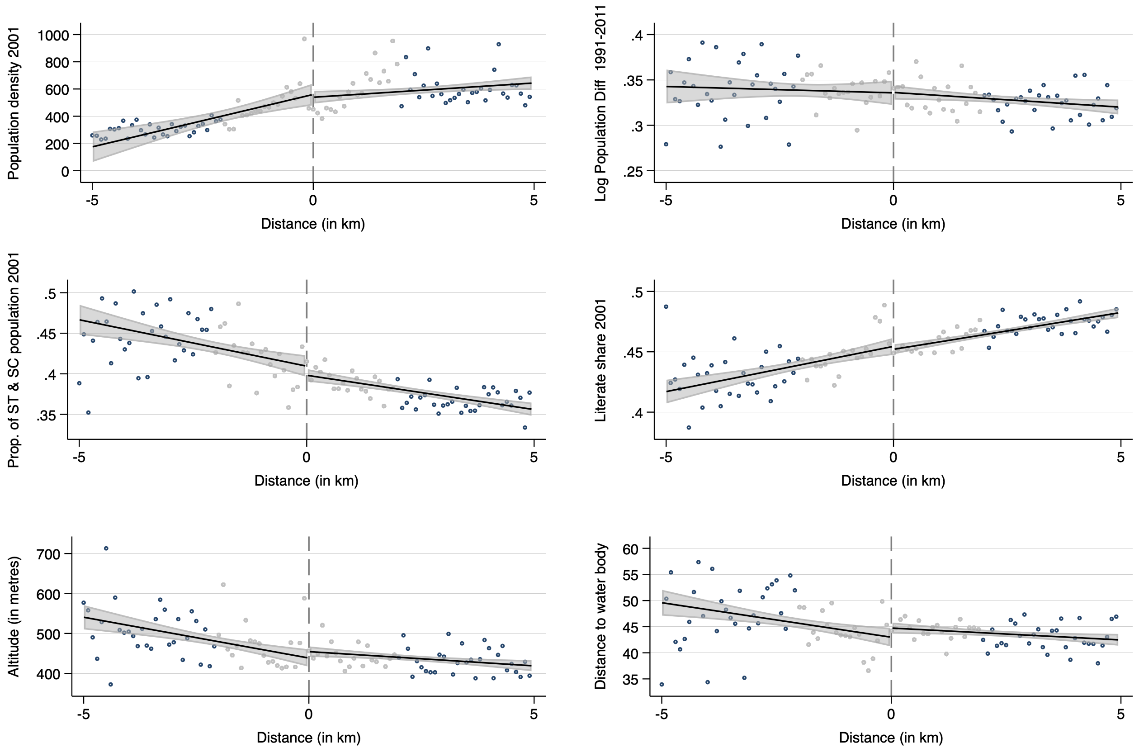
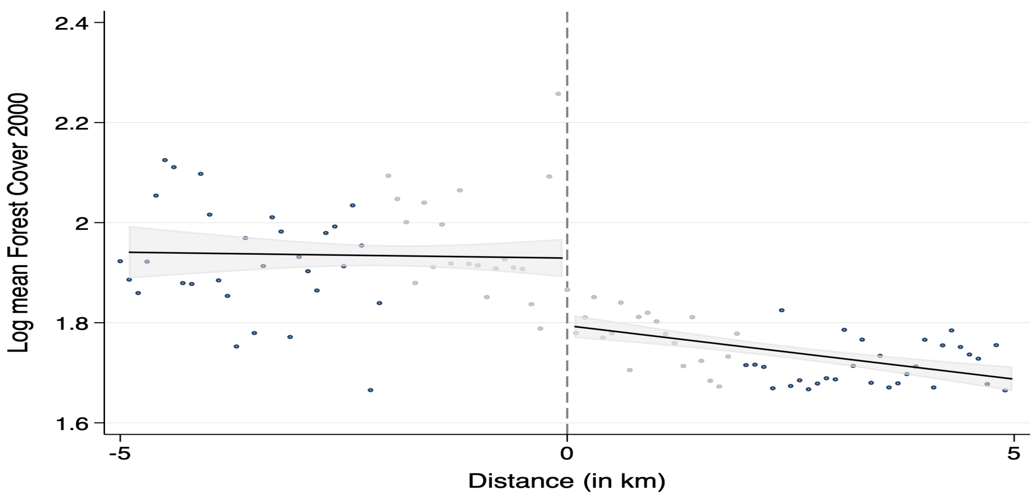


Figure 3.3. Balance of village characteristics

Notes: The figure plots baseline village characteristics over the distance of the village to the closest protected area boundary. Villages inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area. Each dot shows the average outcome within a bin, where bins are chosen by the variance evenly-spaced method estimated using code from Calonico, Cattaneo, and Titiunik (2015). A linear fit is estimated separately for each side of the protected area boundary and the grey shaded region presents the 95% confidence intervals.

(i) Log Forest Cover



(ii) Change in Log Forest Cover

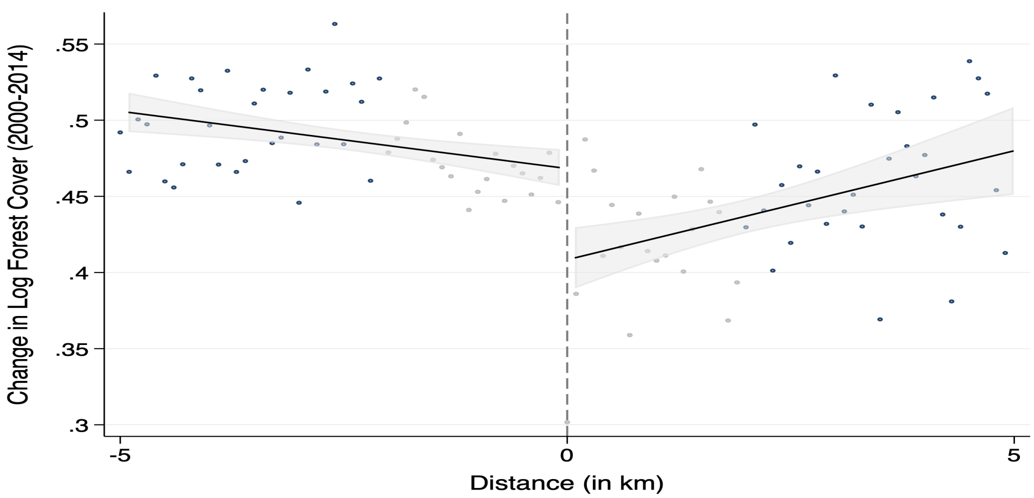
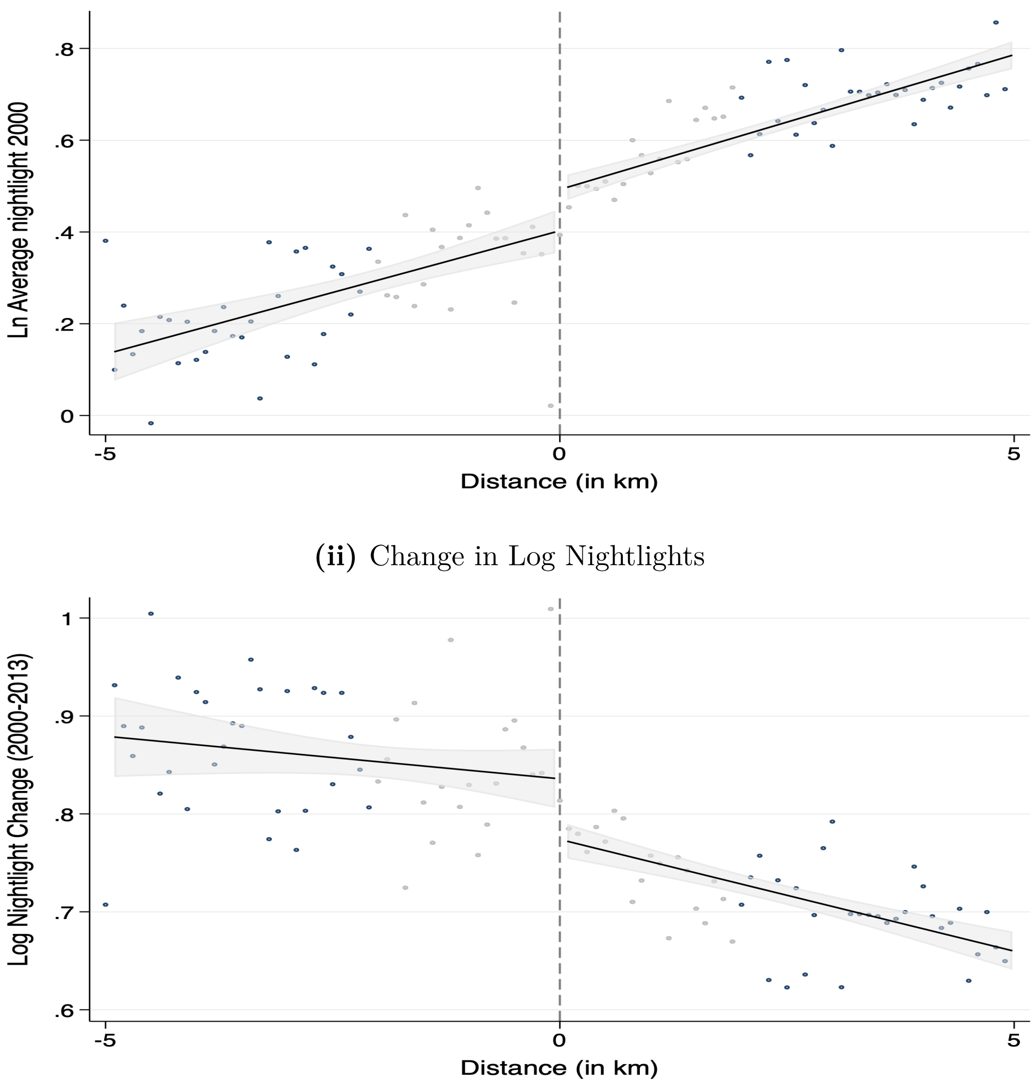


Figure 3.4. Effect of Protected Area on Forest Cover

Notes: The figure plots log forest cover in the year 2000 (panel a) and the change in forest cover between 2000 and 2014 (panel b). Villages inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area.

(i) Log Nightlight

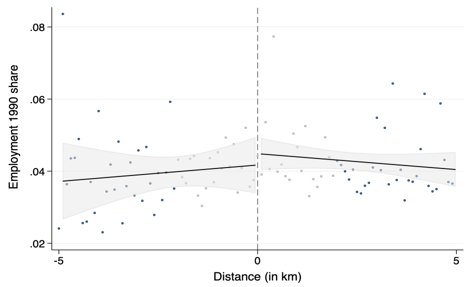


(ii) Change in Log Nightlights

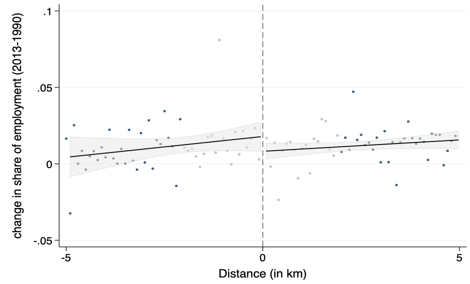
Figure 3.5. Effect of Protected Area on Nightlights

Notes: The figure plots log nightlights in the year 2000 (panel a) and the change in nightlights between 2000 and 2013 (panel b). Villages inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area.

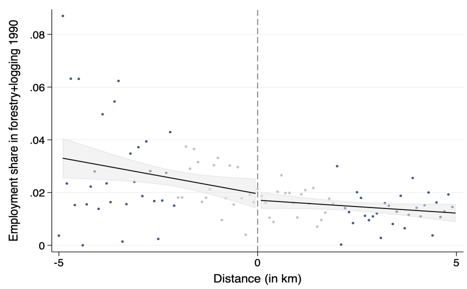
(i) Employment share



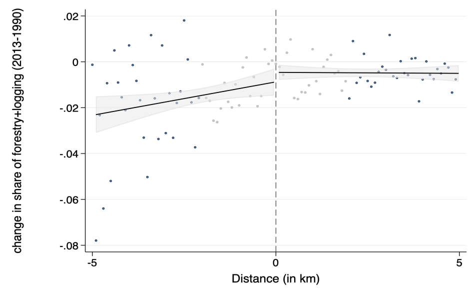
(ii) Change in Employment



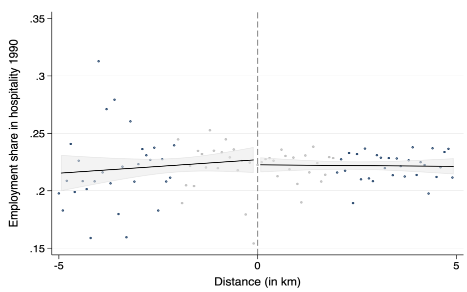
(iii) Employment in Forestry



(iv) Change in Employment in Forestry



(v) Employment in Hospitality



(vi) Change in Employment in Hospitality

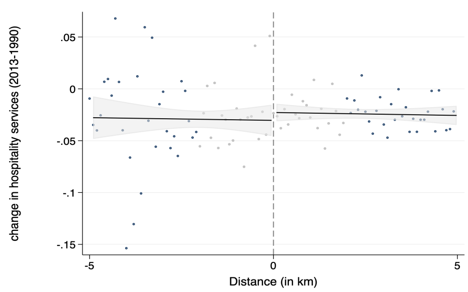


Figure 3.6. Effect of Protected Area on Employment

Notes: The figure presents the RD plots for village-level employment and consumption. Panel a presents share of total population that is employed in formal sector employment, panel b is the change in share of total employment in formal sector employment, panel c is share of total employment in forestry, panel d is the change in share of employment in forestry, panel e is the share of employment in hospitality (tourism, hotels, restaurants), panel f is change in share of employment in the hospital sector, and panel g is the log imputed consumption as measured by SECC. Villages inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area.

Table 3.1. Summary statistics and balance

Variable	Full sample ($\leq$ 5km of PA boundary)	Inside PA	Outside PA	Difference of means	RD estimate	p-value on RD estimate
Scheduled Tribe (share)	0.23	0.22	0.29	0.07	0.009	0.31
Literate (share)	0.46	0.47	0.44	-0.03	0.000	0.94
Population density	544.33	589.46	407.96	-181.50	21.211	0.44
Population growth (1991-2011)	0.33	0.33	0.34	0.01	0.001	0.87
Altitude	448.35	437.55	479.04	41.48	-8.988	0.46
Distance to river	44.16	43.65	45.61	1.95	-1.510	0.14
Distance from nearest town (km)	48.41	46.94	52.84	5.90	0.238	0.73
N	31917	23980	7937			

Notes: The table presents mean values for village characteristics, measured in the baseline period. Columns 1-3 show the unconditional means for all villages within 5km of PA boundary, villages inside PAs, and villages outside PAs, respectively. Column 4 shows the difference of means across Columns 2 and 3. Column 5 shows the regression discontinuity estimate, following the main estimating equation in section 3.4, of the effect of being in PAs on the baseline variable, and Column 6 is the p-value for this estimate. An optimal bandwidth of 5km around the PA boundary has been used.

Table 3.2. Effect of Protected areas on forest cover and nightlights

	Forest Cover		Nightlights	
	Log Forest Cover 2000	Δ Log Forest Cover (2014-2000)	Log Nightlight 2000	Δ Log Nightlight (2013-2000)
$1[Dis_{v,d} < 0]$	0.32***	0.04*	-0.28***	0.16***
	(0.09)	(0.02)	(0.09)	(0.05)
Villages	36089	36063	33331	33331
Protected areas	373	373	363	363
Mean (outside)	1.7	0.4	0.6	0.7
Mean (inside)	1.9	0.5	0.3	0.9

Notes: This table presents the RD results of being in the PA boundary on the village ecological and economic outcomes. Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). The dependent variable in the first and third columns are the log forest cover and the log nightlight in the year 2000, respectively. The second and fourth columns refer to the change in log forest cover and log nightlights between 2000 and 2014. All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

Table 3.3. Effect of Protected areas on consumption and employment

	Log Consumption SECC (2011)	Employment share (1990)	Δ employment (2013-1990)	Employment-Forestry 1990	Δ Forestry Employment (2013-1990)	Employment-Hospitality 1990	Δ Hospitality Employment (2013-1990)
$1[Dis_{v,d} < 0]$	0.02	-0.00	0.00	-0.01	-0.00	-0.06	0.04*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.02)
Villages	30086	24677	23404	21971	20892	21971	20892
Protected areas	354	302	293	298	298	293	294
Mean (outside)	9.7	0.0	0.0	0.0	-0.0	0.2	-0.0
Mean (inside)	9.7	0.0	0.0	0.0	-0.0	0.2	-0.0

Notes: This table presents the RD results of being in the PA boundary for the village-level employment and consumption measures. Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). The dependent variable in the first column is the log imputed consumption from the SECC. Columns 2-3 present effects on employment share in the formal sector (measured using total employment in the formal sector divided by the total population) and changes in employment share. Columns 4-5 present the effects on levels and changes in the share of employment in forestry, respectively. Columns 6-7 present the effects on levels and changes in the share of employment in the hospitality sector (comprising of tourism, hotels, and restaurants). All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

Table 3.4. Effect of Protected Areas on Forest Cover

PANEL A: Log Forest Cover (2000)

	$\geq$ 70% inside	$\geq$ 50% inside	Old PAs (pre 1985)	Sanctuaries	National Parks	Large PAs	Forestry share of state GDP (top 50 percentile)	State expenditure on Forestry (top 50 percentile)
$1[Dis_{v,d} < 0]$	0.32***	0.18***	0.32***	0.33***	0.19	0.12	0.02	0.12
	(0.09)	(0.06)	(0.09)	(0.09)	(0.20)	(0.09)	(0.03)	(0.09)
Villages	36089	36090	25697	31894	4195	23229	26444	30302
Protected areas	357	356	242	298	61	180	265	358
Mean (outside)	1.7	1.7	1.7	1.7	2.1	1.7	1.9	1.9
Mean (inside)	1.9	1.9	1.9	1.9	2.3	1.9	2.1	2.2

PANEL B: Change in Log Forest Cover (2014-2000)

	$\geq$ 70% inside	$\geq$ 50% inside	Old PAs (pre 1985)	Sanctuaries	National Parks	Large PAs	Forestry share of state GDP (top 50 percentile)	State expenditure on Forestry (top 50 percentile)
$1[Dis_{v,d} < 0]$	0.04*	0.02	0.05**	0.05*	0.04	0.10**	-0.02***	0.08***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.01)	(0.03)
Villages	33331	33331	25697	29290	4041	21657	24373	27298
Protected areas	359	360	242	299	61	181	277	367
Mean (outside)	0.4	0.4	0.4	0.4	0.3	0.4	0.4	0.4
Mean (inside)	0.5	0.5	0.5	0.5	0.3	0.5	0.5	0.5

Notes: This table presents the RD results of being in the PA boundary on village-level log forest cover in panel (a) and the change in log forest cover between 2000 and 2014 in panel (b). Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). In the first column, only villages with greater than 70% overlap with protected areas are considered *treated*. In the second column, we change this to villages with greater than 50% overlap with protected areas. In column 3, we run the analysis on subsample of villages in older protected areas established before 1985. Columns 4,5, and 6 present the estimation for sanctuaries, national parks, and protected areas that are in the top 50 percentile of the size distribution, respectively. In column 7, we restrict the analysis to protected areas in states where the share of GDP from forestry and logging falls within the top 50th percentile. In column 8, we focus on protected areas in states where the share of expenditure on forestry is within the top 50th percentile. All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

Table 3.5. Effect of Protected Areas on Nightlights

PANEL A: Log Nightlights (2000)

	$\geq$ 70% inside	$\geq$ 50% inside	Old PAs (pre 1985)	Sanctuaries	National Parks	Large PAs	Forestry share of state GDP (top 50 percentile)	State expenditure on Forestry (top 50 percentile)
$1[Dis_{v,d} < 0]$	-0.28***	-0.25***	-0.31***	-0.34***	-0.16	-0.24***	-0.20***	-0.29***
	(0.09)	(0.06)	(0.09)	(0.10)	(0.20)	(0.09)	(0.06)	(0.08)
Villages	33331	33331	23823	29290	4041	21657	24373	27298
Protected areas	359	360	235	299	61	181	277	367
Mean (outside)	0.6	0.7	0.6	0.7	0.6	0.6	0.6	0.6
Mean (inside)	0.3	0.3	0.3	0.4	0.2	0.3	0.3	0.2

PANEL B: Change in Log Nightlights (2014-2000)

	$\geq$ 70% inside	$\geq$ 50% inside	Old PAs (pre 1985)	Sanctuaries	National Parks	Large PAs	Forestry share of state GDP (top 50 percentile)	State expenditure on Forestry (top 50 percentile)
$1[Dis_{v,d} < 0]$	0.16***	0.08***	0.19***	0.19***	0.03	0.12**	0.20**	0.41***
	(0.05)	(0.03)	(0.06)	(0.05)	(0.09)	(0.05)	(0.10)	(0.11)
Villages	33331	33331	23823	29290	4041	21657	24373	27298
Protected areas	359	360	235	299	61	181	277	367
Mean (outside)	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.8
Mean (inside)	0.9	0.8	0.9	0.8	1.0	0.9	0.9	1.0

Notes: table presents the RD results of being in the PA boundary on village-level log nightlights in panel (a) and the change in log nightlights between 2000 and 2013 in panel (b). Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). In the first column, only villages with greater than 70% overlap with protected areas are considered *treated*. In the second column, we change this to villages with greater than 50% overlap with protected areas. In column 3, we run the analysis on subsample of villages in older protected areas established before 1985. Columns 4,5, and 6 present the estimation for sanctuaries, national parks, and protected areas that are in the top 50 percentile of the size distribution, respectively. In column 7, we restrict the analysis to protected areas in states where the share of GDP from forestry and logging falls within the top 50th percentile. In column 8, we focus on protected areas in states where the share of expenditure on forestry is within the top 50th percentile. All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

Table 3.6. Effect of Protected areas on consumption and employment

	$\geq$ 70% inside	$\geq$ 50% inside	Old PAs (pre 1985)	Sanctuaries	National Parks	Large PAs	Forestry share of state GDP (top 50 percentile)	State expenditure on Forestry (top 50 percentile)
PANEL A: Employment Share (1990)								
$1[Dis_{v,d} < 0]$	-0.00	-0.01	-0.00	-0.00	0.02	0.03**	0.07**	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)
PANEL B: Forestry Employment Share (1990)								
$1[Dis_{v,d} < 0]$	-0.01	0.00	-0.00	-0.00	-0.01	0.02**	0.02**	0.03***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
PANEL C: Hospitality Employment Share (1990)								
$1[Dis_{v,d} < 0]$	-0.06	-0.02	-0.06	-0.07	-0.00	-0.01	-0.01	-0.03
	(0.05)	(0.01)	(0.06)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)
Villages	21971	21971	15459	19401	2570	14137	15224	16885
Protected areas	368	371	241	310	61	180	265	351
PANEL D: Log Consumption (2011)								
$1[Dis_{v,d} < 0]$	0.02	-0.00	0.01	0.04*	-0.06	0.04**	0.09***	0.05***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)
Villages	30086	30086	21434	26554	3532	19369	25797	21581
Protected areas	364	370	241	305	61	181	349	293

Notes: This table presents the RD results of being in the PA boundary on the share of total population which is in formal sector employment in panel (a), the share of employment in forestry and hospitality (tourism, hotels, restaurants) sector in panel (b) and (c), and log imputed consumption in panel (d). Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). In the first column, only villages with greater than 70% overlap with protected areas are considered *treated*. In the second column, we change this to villages with greater than 50% overlap with protected areas. In column 3, we run the analysis on subsample of villages in older protected areas established before 1985. Columns 4,5, and 6 present the estimation for sanctuaries, national parks, and protected areas that are in the top 50 percentile of the size distribution, respectively. In column 7, we restrict the analysis to protected areas in states where the share of GDP from forestry and logging falls within the top 50th percentile. In column 8, we focus on protected areas in states where the share of expenditure on forestry is within the top 50th percentile. All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

Table 3.7. Effect of Protected areas on employment growth

	$\geq$ 70% inside	$\geq$ 50% inside	Old PAs (pre 1985)	Sanctuaries	National Parks	Large PAs	Forestry share of state GDP (top 50 percentile)	State expenditure on Forestry (top 50 percentile)
	PANEL A: Change in Employment Share (2013-1990)							
$1[Dis_{v,d} < 0]$	0.00	0.00	0.00	0.01	0.00	0.01	0.04*	0.06*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
	PANEL B: Change in Forestry Employment Share (2013-1990)							
$1[Dis_{v,d} < 0]$	-0.00	-0.00	-0.01	-0.01	-0.00	0.02	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	PANEL C: Change in Hospitality Employment Share (2013-1990)							
$1[Dis_{v,d} < 0]$	0.04*	0.02	0.04*	0.04*	0.03	0.03	0.03	0.06**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)
Villages	21971	21971	15459	19401	2570	14137	15224	16885
Protected areas	368	371	241	310	61	180	265	351

Notes: This table presents the RD results of being in the PA boundary on the change in share of total population which is in formal sector employment (between 1990 and 2013) in panel (a) and the change in share of employment in forestry and hospitality (tourism, hotels, restaurants) sectors in panel (b) and (c). Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). In the first column, only villages with greater than 70% overlap with protected areas are considered *treated*. In the second column, we change this to villages with greater than 50% overlap with protected areas. In column 3, we run the analysis on subsample of villages in older protected areas established before 1985. Columns 4,5, and 6 present the estimation for sanctuaries, national parks, and protected areas that are in the top 50 percentile of the size distribution, respectively. In column 7, we restrict the analysis to protected areas in states where the share of GDP from forestry and logging falls within the top 50th percentile. In column 8, we focus on protected areas in states where the share of expenditure on forestry is within the top 50th percentile. All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

Table 3.8. Effect of PAs on forest cover by terciles of government share of expenditure on forestry

Outcome: Change in Log Forest cover (2000-2014)

	Bottom tercile	Middle tercile	Top tercile
$1[Dis_{v,d} < 0]$	-0.03	-0.01	0.15*
	(0.04)	(0.02)	(0.08)
Villages	9985	10775	11703
Protected areas	173	105	149
Mean (outside)	0.4	0.6	0.5
Mean (inside)	0.4	0.5	0.5

Notes: This table presents the RD results for change in log forest cover for protected areas in states in different tercile distributions of their share of total expenditure on forestry. Over the 13-year period, states that spent the highest share on forestry (top tercile, column 3) were Kerala, Madhya Pradesh, Himachal Pradesh, Karnataka, and Jammu and Kashmir. Those on the bottom tercile (column 1) were Andhra Pradesh, Maharashtra, Rajasthan, Gujarat, and Tamil Nadu. We run the estimation separately for states in different terciles. Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$).

3.9 Additional Figures and Tables

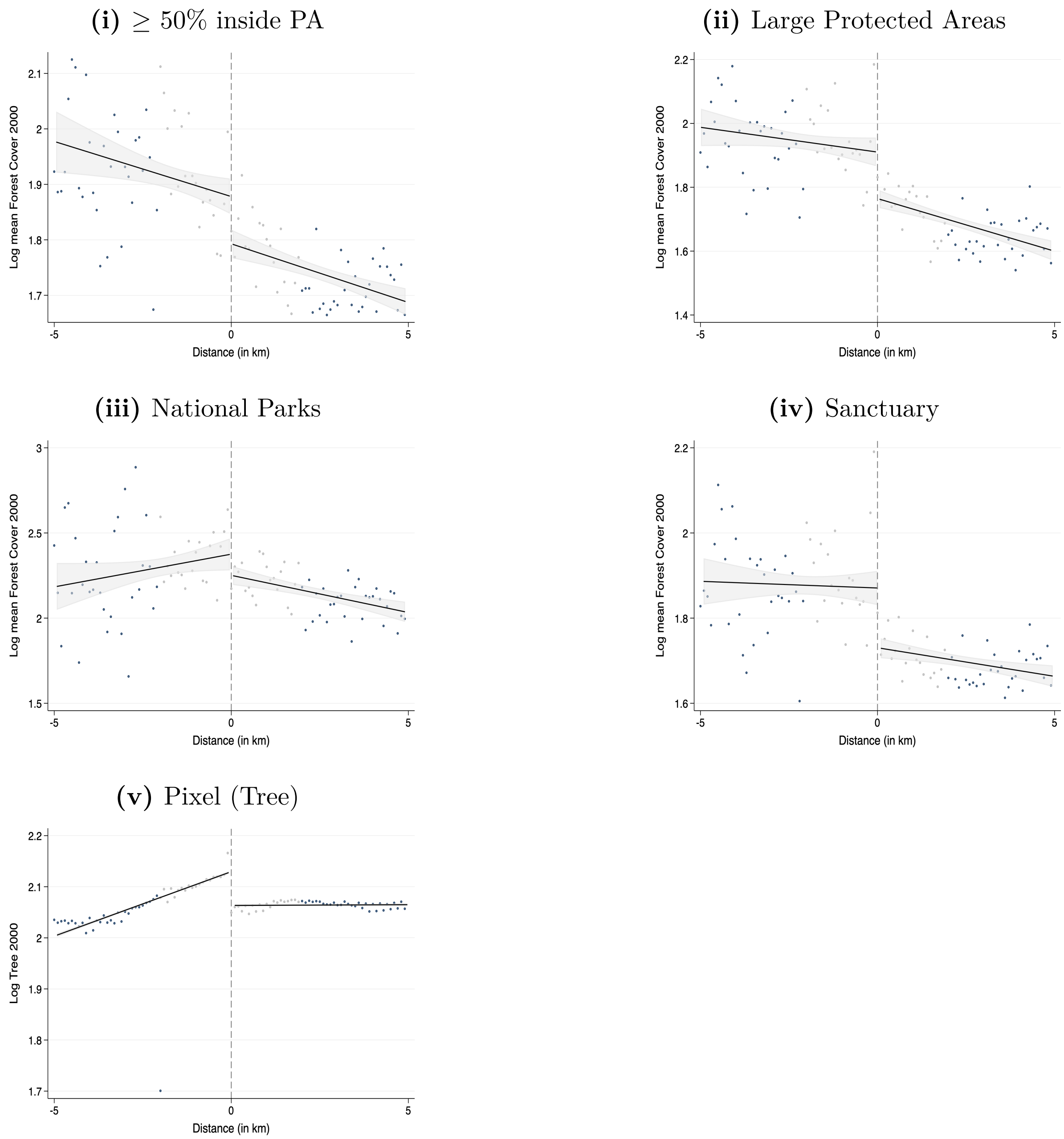


Figure 3.A.1. Effect of Protected Area on Forest Cover

Notes: The figure plots log forest cover in the year 2000 against the distance to PA boundary. Points inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area. Panel a presents villages with greater than 50% overlap of land area with protected areas; in panel b, we present villages in protected areas that are in the top 50 percentile of the size distribution; panel c and d have villages restricted to areas with national parks and wildlife sanctuaries, respectively. In panel e, the level of granularity is at the pixel-level.

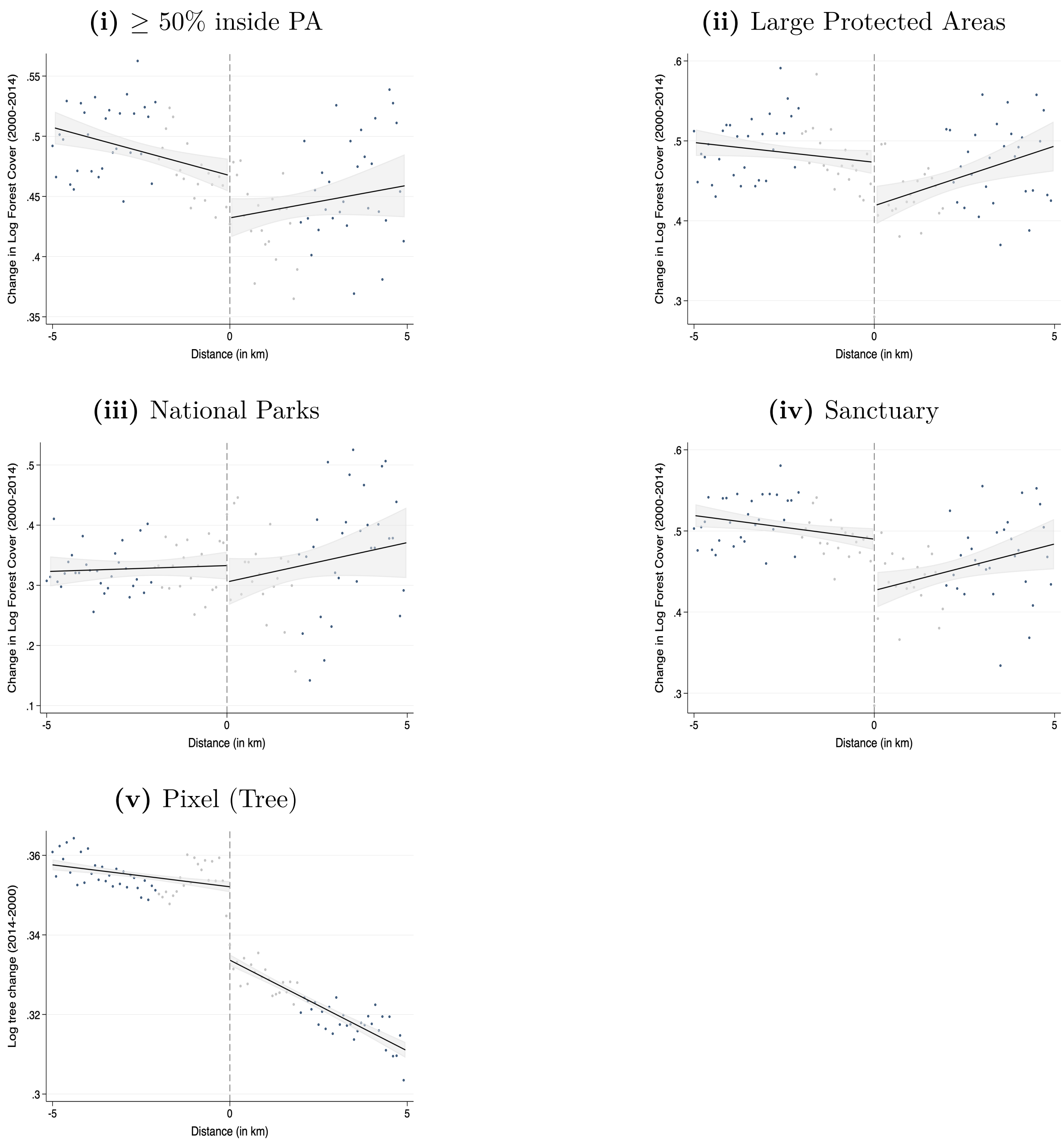


Figure 3.A.2. Effect of Protected Area on Change in Forest Cover

Notes: The figure plots change in log forest cover between 2000 and 2014 against the distance to PA boundary. Points inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area. Panel a presents villages with greater than 50% overlap of land area with protected areas; in panel b, we present villages in protected areas that are in the top 50 percentile of the size distribution; panel c and d have villages restricted to areas with national parks and wildlife sanctuaries, respectively. In panel e, the level of granularity is at the pixel-level.

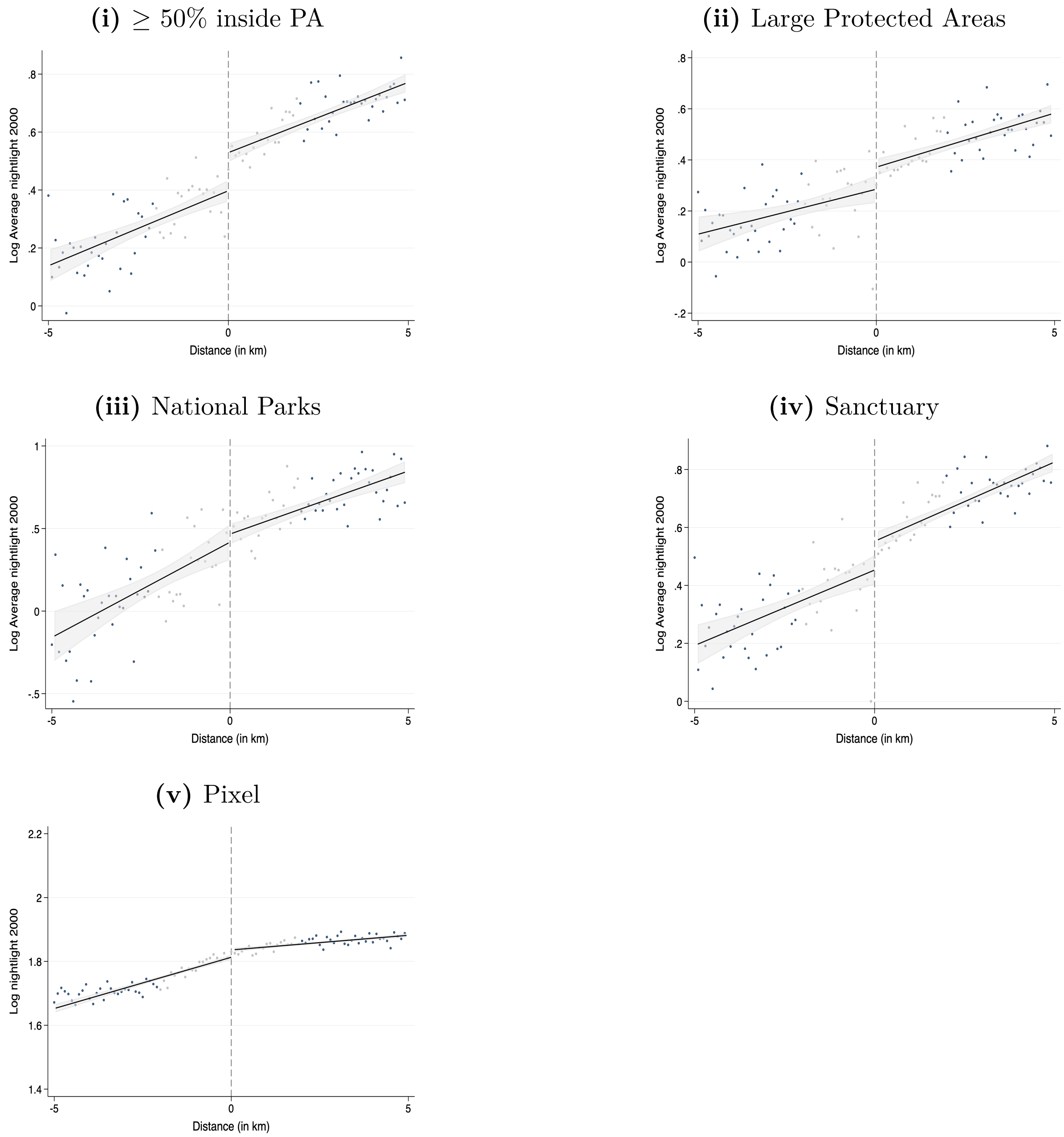


Figure 3.A.3. Effect of Protected Area on Nightlights

Notes: The figure plots log nightlights in the year 2000 against the distance to PA boundary. Points inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area. Panel a presents villages with greater than 50% overlap of land area with protected areas; in panel b, we present villages in protected areas that are in the top 50 percentile of the size distribution; panel c and d have villages restricted to areas with national parks and wildlife sanctuaries, respectively. In panel e, the level of granularity is at the pixel-level.

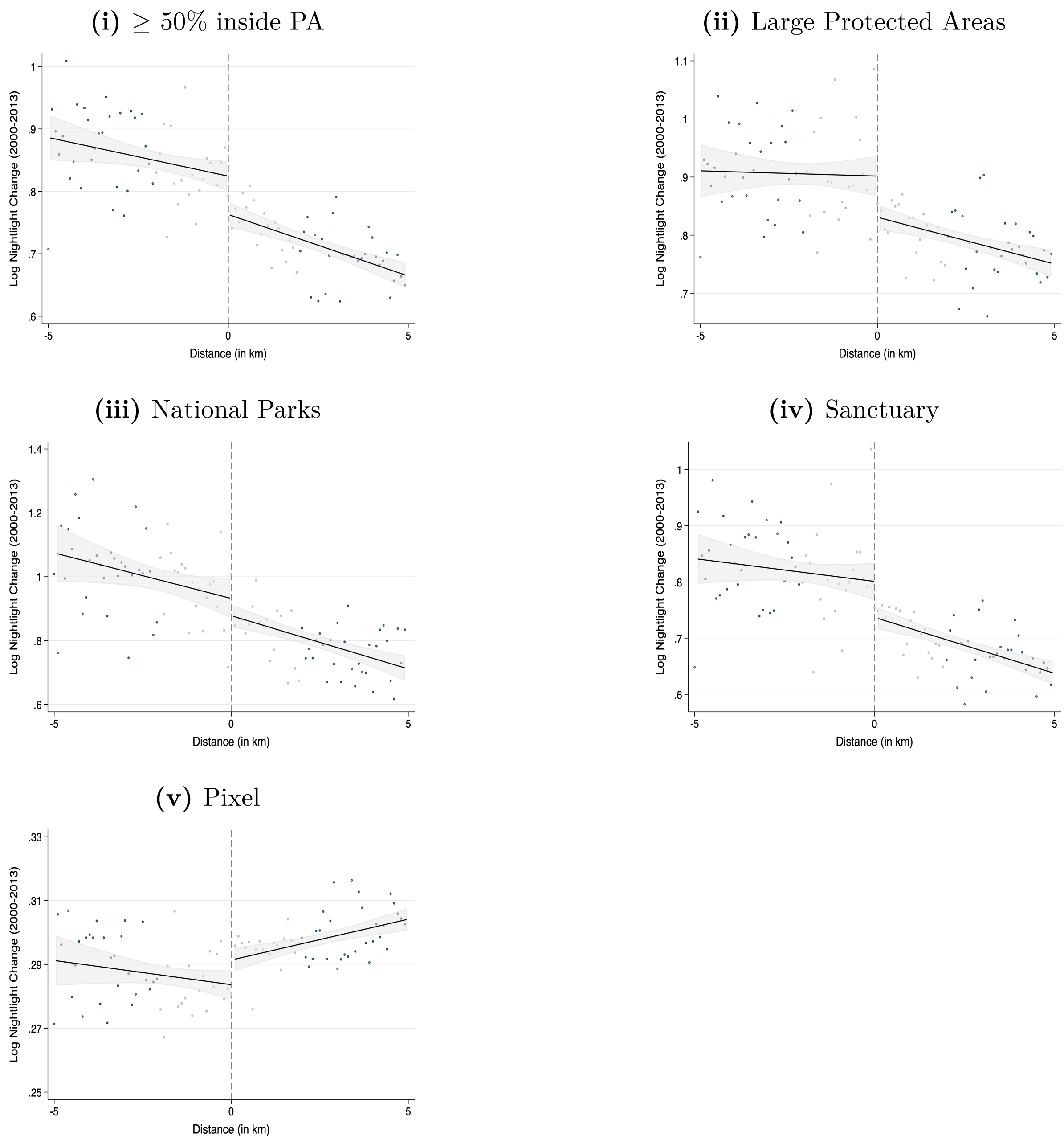


Figure 3.A.4. Effect of Protected Area on Change in Nightlights

Notes: The figure plots change in log nightlights between 2000 and 2013 against the distance to PA boundary. Points inside a protected area are coded as negative distance (left of the 0 threshold). Points to the right of the zero distance threshold are outside the protected area. Panel a presents villages with greater than 50% overlap of land area with protected areas; in panel b, we present villages in protected areas that are in the top 50 percentile of the size distribution; panel c and d have villages restricted to areas with national parks and wildlife sanctuaries, respectively. In panel e, the level of granularity is at the pixel-level.

Table 3.A.1. Effect of Protected areas using pixel-level data

	Forest Cover				Nightlights	
	Tree cover (2000)	Non Tree Veg (2000)	Δ Tree cover (2000-2013)	Δ NonTree cover (2000-2013)	Nightlights (2000)	Δ nightlights (2000-2013)
$1[Dis_{v,d} < 0]$	0.09***	0.00	0.02***	0.00***	-0.02***	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Villages	9634283	1.02e+07	9276559	1.02e+07	149721	124377
Mean (outside)	2.1	4.0	0.3	0.0	1.9	0.6
Mean (inside)	2.2	4.0	0.3	0.0	1.8	0.6

Notes: The table presents RD estimates from analysis at the pixel-level. Column 1 presents effect on log forest tree cover in the year 2000, column 2 presents the effects on log non-tree vegetation cover in year 2000, the dependent variables in column 3-4 are the change in log tree cover and log non-tree between 2000 and 2013, columns 5-6 are levels and changes in log nightlights. The specification includes protected area fixed effects (see section 3.4 for details).

Table 3.A.2. Effect of Protected areas on forest cover and nightlights on Protected areas formed after 2010

	Forest Cover		Nightlights	
	Log Forest Cover 2000	Δ Log Forest Cover (2014-2000)	Log Nightlight 2000	Δ Log Nightlight (2013-2000)
$1[Dis_{v,d} < 0]$	0.59***	-0.02	-0.10	0.02
	(0.18)	(0.12)	(0.42)	(0.22)
Villages	2222	2222	1984	1984
Protected areas	29	29	29	29
Mean (outside)	2.2	0.4	1.2	0.5
Mean (inside)	2.4	0.4	0.7	0.7

Notes: This table presents the RD results of being in the PA boundary for the village ecological and economic outcomes. The sample is restricted to protected areas established between 2010 and 2018. Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). The dependent variable in the first and third columns are the log forest cover and the log nightlight in the year 2000, respectively. The second and fourth columns refer to the change in log forest cover and log nightlights between 2000 and 2014. All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

Table 3.A.3. Effect of Protected areas on consumption and employment on Protected areas formed after 2010

	Log Consumption SECC (2011)	Employment share (1990)	Δ employment (2013-1990)	Employment-Forestry 1990	Δ Forestry Employment (2013-1990)	Employment-Hospitality 1990	Δ Hospitality Employment (2013-1990)
$1[Dis_{v,d} < 0]$	0.06	0.04	-0.03	-0.02	0.01	-0.04	-0.01
	(0.06)	(0.03)	(0.04)	(0.01)	(0.01)	(0.05)	(0.06)
Villages	1837	1661	1636	1588	1561	1588	1561
Protected areas	29	27	25	24	26	26	27
Mean (outside)	10.0	0.1	0.0	0.0	-0.0	0.2	-0.0
Mean (inside)	9.9	0.1	0.0	0.0	0.0	0.2	-0.1

Notes: This table presents the RD results of being in the PA boundary for the village-level employment and consumption measures. The sample is restricted to protected areas established between 2010 and 2018. Villages inside PA are coded as negative distance to PA boundary ($1[Dis_{v,d} < 0]$). The dependent variable in the first column is the log imputed consumption from the SECC. Columns 2-3 present effects on employment share in the formal sector (measured using total employment in the formal sector divided by the total population) and changes in employment share. Columns 4-5 present the effects on levels and changes in the share of employment in forestry, respectively. Columns 6-7 present the effects on levels and changes in the share of employment in the hospitality sector (comprising of tourism, hotels, and restaurants). All outcomes are at the village-level. The specification includes baseline village-level controls for demographics and size, as well as protected area fixed effects (see section 3.4 for details).

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