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## Regional Autonomy and Development: Evidence from Madhya Pradesh – Chhattisgarh Split in India

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# Regional Autonomy and Development: Evidence from Madhya Pradesh – Chhattisgarh Split in India\*

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## Abstract

We exploit the creation of Chhattisgarh (CH) from Madhya Pradesh (MP) in 2000 as a natural experiment to study how regional autonomy affects economic development through administrative proximity and political accountability. Using both difference-in-differences and difference-in-discontinuities designs, we compare villages straddling the new state border before and after the split. Villages in CH near the border experienced significantly faster economic growth—measured by nighttime lights, expansion of private firms and non-farm employment, and improved provision of public goods—than comparable MP villages. These gains are not explained by political stability, party ideology, or migration. Instead, they arise from a more responsive local elite in-charge of the new administration as well as closer proximity to the new state capital, Raipur, which enhanced bureaucratic oversight and political accountability. The results demonstrate that the geography of administration—the distance between citizens and state institutions—can shape development outcomes as powerfully as formal political institutions.

JEL Codes: D72, H41, H70, H77, O10, O40

Keywords: state autonomy and control, responsive governance, economic development, proximity, capital, accountability

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## I. Introduction

Scholars have long argued that granting greater autonomy and control to subnational regions—a central feature of political decentralization—can accelerate local economic development by making governance more responsive and accountable. At the same time, decentralization may increase the risk of elite capture, rent-seeking, political instability, and corruption. Whether decentralization improves or worsens developmental outcomes is ultimately an empirical question, and it depends on how changes in control and autonomy reshape incentives and accountability.<sup>1</sup>

This paper exploits a major decentralization episode in India—the creation of Chhattisgarh (CH) from Madhya Pradesh (MP) in 2000—as a natural experiment. The bifurcation transferred control and autonomy over the CH region to a new state administration and leadership (a new government and Chief Minister). We use this setting to examine how a change in regional autonomy and control affects the development trajectory of the affected region.

In India's federal structure, state governments enjoy substantial autonomy over public service delivery, governance, law and order, and economic planning. They can also constitute independent bureaucratic and regulatory institutions to implement and oversee these functions. The creation of a new state therefore reallocates administrative authority, redefines accountability relationships, and opens new channels for political responsiveness.

The formation of CH was unusual in several respects. Unlike many statehood movements in India, it was elite-driven and largely peaceful, and the new CH–MP border followed existing district boundaries (Tillin, 2013), minimizing conflict over territorial demarcation. This helps reduce concerns about endogenous border placement. On the political front, both CH and MP retained stable two-party systems dominated by the Indian National Congress (INC) and the Bharatiya Janata Party (BJP), with no strong regional parties before or after the split. After 2003, the BJP governed both states continuously until 2018, and each state was led by a long-serving Chief Minister (CM) over this period (Shivraj Singh Chouhan in MP, Raman Singh in CH). This symmetry sharply limits confounding from differences in party ideology, political stability, or the emergence of state-level regional parties.

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<sup>1</sup> See Bardhan (2002), Bardhan and Mookherjee (2006), Faguet (2004, 2014), Singhania (2022), Grossman et al. (2017), and Grossman and Lewis (2014) for a review on this form of decentralization that results in a transfer of regional autonomy and control to local leaders and governments.

The CH–MP split thus provides a useful laboratory to study how transferring regional control and autonomy affects development, holding constant the broader party system and political environment. It also offers an opportunity to understand why neighboring regions with similar institutional histories diverge in their development trajectories.

Trends in per capita Net State Domestic Product (NSDP) between 1993 and 2013, which cover both the pre-split (1993–2000) and post-split (2001–2013) periods, reveal a clear divergence between CH and MP after 2000 (Figure 1).<sup>2</sup> In this paper, we argue that this divergence reflects the effect of transferring autonomy and control over the CH region to a new state administration and leadership. Our goal is to identify the causal impact of this change in governance structure on local economic development as well as the underlying mechanisms.

To do so, we compare villages on either side of the new CH–MP state border before and after the split using a difference-in-differences (DiD) and a difference-in-discontinuities (DiDC) framework. Our primary outcome is satellite-based nighttime luminosity, which we use as a proxy for local economic development at the village level.<sup>3</sup> We complement this with village-level measures of non-agricultural firm activity, nonfarm employment, delivery of public goods, and efficiency in rural infrastructure program implementation—strong correlates of development documented in recent work (Asher et al., 2021).

Rather than comparing all villages in CH and MP—an approach that would confound the effect of the split with long-standing differences in geography, resource endowments, and infrastructure—we restrict attention to villages close to and on either side of the new border. This “border sample” leverages the continuity in geography, climate, and initial economic conditions across the border, and thus allows us to more credibly isolate the causal impact of the split.

Our analysis shows that villages under CH’s new administration experienced significantly higher growth in nighttime lights relative to comparable villages in MP across the border in the post-split period. In other words, CH villages near the border grew faster than their MP

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<sup>2</sup> Using Per Capita NSDP (Constant Prices) data from the RBI Handbook of Statistics on Indian States, we calculate and compare the average annual growth rate of Per Capita NSDP of the two states separately before and after the bifurcation. Before the split, average annual growth rate of Per Capita NSDP of CH state was -0.66% and that of MP state was 1.88% i.e., MP was growing faster than CH region by 2.54 pp. After the split, average annual growth rate of NSDP of CH state was 6.12% and that of MP state was 4.71% i.e., CH’s growth rate was now 6.78 pp higher than its growth rate before the split and was now 1.41 pp higher than MP.

<sup>3</sup> Due to a lack of income data at the village-level spanning periods before and after the creation of CH, we use satellite nighttime lights data as a proxy for economic activity. Several other studies use nighttime lights as a proxy for economic activity. See Henderson et al. (2018), Michalopoulos and Papaioannou (2014), Pinkovskiy (2017), Chanda and Kabiraj (2020), Jha and Talathi (2023, 2024), and Li et al. (2020).

counterparts after statehood, relative to the pre-split period when both sides were governed by MP. Using an elasticity of per capita income with respect to nighttime lights density from the existing literature<sup>4</sup>, our estimates imply a gain in per capita income of roughly 24 – 40 percent. We corroborate this with evidence of substantial increases in non-agricultural private-sector activity and nonfarm employment, improved provision of essential public goods—schools, health care, telecommunication, and electricity—and greater efficiency and productivity in the implementation of rural infrastructure programs such as the Pradhan Mantri Gram Sadak Yojana (PMGSY) in CH villages near the border.

A key factor behind CH’s superior performance is proximity to the state administration. Decentralization that brings the government “closer to the people” can expand the set of groups whose interests are represented and increase the reach of the state (Faguet et al., 2015; Grossman et al., 2017; Grossman and Lewis, 2014). In our setting, the creation of CH substantially reduced the average distance between border villages and their state capital: from about 450–480 km to Bhopal before the split to about 137–152 km to Raipur after the split. MP villages near the border remained the same distance from Bhopal before and after the split. We show that this sharp reduction in distance for CH villages is central to understanding their better performance in the post-split period.

We then ask how bringing the government closer translates into more responsive governance. Since the creation of CH created space for the rise of popular local leaders, particularly lower-caste elites (Tillin, 2013), we examine whether inclusion in the state-building process increased the accountability of local leaders to their constituents. Using measures of participation (voter turnout) and competitiveness (winning margin) in state legislative elections within a DiD framework, we find that electoral competitiveness rose significantly more in CH than in MP after the split, consistent with greater accountability. Evidence on voter turnout is less robust and should be interpreted with more caution.

Our findings show that granting regional autonomy and control can improve economic outcomes by reshaping incentives. Newly empowered leaders operate closer to their constituents, face greater scrutiny, and are more accountable. Administrative proximity and more competitive politics offer a tractable mechanism for the observed divergence in development between CH and

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<sup>4</sup> An elasticity estimate of 0.22 is used for level of per capita income with respect to nighttime lights density. See Jha and Talathi (2024) and Henderson et al. (2012) for more information on elasticity estimates.

MP. While our analysis focuses on a newly created state, the underlying mechanism is more general – it applies to any setting where regions are brought closer to the seat of administration and where electoral institutions generate meaningful accountability.<sup>5,6</sup>

In the context of India, our paper relates to several studies that use the 2000 state splits as a source of variation. Krishnamurthy et al. (2017) examine the impact of food price subsidies on household nutrition in the backdrop of public distribution system (PDS) reforms that dramatically increased the availability of PDS grains in CH. Comparing CH households to those in bordering districts that did not experience the reform, they find sizable improvements in nutritional intake in CH. Chhotray et al. (2020) compare the prioritization of the PDS in the newly created states of CH and Jharkhand and attribute CH’s stronger performance to the interaction of stable political leadership, bureaucratic capacity, and state–society collaboration—interpretations consistent with our findings on the importance of proximity and accountability. Shenoy (2018) studies place-based policies in Uttarakhand using a spatial discontinuity design; Dhillon et al. (2020) analyze how secession affects the comparative performance of natural-resource-rich and natural-resource-poor areas, and, for the CH–MP split, find no statistically significant differential effect between these areas, helping rule out resource composition as a primary confounder. Vaibhav and Ramaswamy (2024) examine the effect of secession on the economic performance of the three new states created in 2000 and their parent states using state-level GDP data and synthetic control and DiD designs; for CH they find a positive but statistically insignificant effect.

Our study differs from this literature in several dimensions. First, we analyze the impact of granting regional autonomy and control on economic development using village-level data, the smallest geographical unit and lowest administrative tier in India. Second, we document a robust and sizable positive effect of the new administration and leadership on a broad set of development indicators—nighttime lights, non-agricultural firm activity, nonfarm employment, public goods provision, and implementation efficiency of rural infrastructure programs—for villages near the border. Third, we provide new empirical evidence on mechanisms, focusing on administrative

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<sup>5</sup> Other studies showing decentralization and its feature of bringing government “closer to the people” to be an important determinant of responsive governance and political accountability include Stansel (2005), Barankay and Lockwood (2007), Faguet (2004, 2014), Hatfield and Kosec (2013), Faguet and Sanchez (2014), Grossman and Lewis (2014), Faguet et al. (2015), Grossman et al. (2017), and Singhania (2022).

<sup>6</sup> Our paper is also related to the various consequences of the limited penetration and reach of the State in remote areas physically more distant from it such as decay in law enforcement (Michalopoulos and Papaioannou, 2014), misgovernance (Campante et al., 2019), greater corruption (Campante and Do, 2014), irregular monitoring of infrastructure quality (Asher et al., 2018), and lower nighttime lights (Provenzano, 2024). In this regard, our paper is closest to Michalopoulos and Papaioannou (2014), Asher et al. (2018), and Provenzano (2024) who investigate this subject in a border discontinuity framework.

proximity and electoral accountability, which have received less attention in previous work on Indian state splits.

The remainder of the paper proceeds as follows: Section II provides background on the CH–MP split; Section III discusses the research design and data; Section IV presents empirical findings and robustness checks; Section V explores mechanisms; and Section VI concludes.

## **II. Background and Context: The Creation of CH from MP**

The state of Chhattisgarh (CH) was carved out of Madhya Pradesh (MP) on November 1, 2000. The reorganization was part of a broader national exercise that also created Jharkhand and Uttarakhand, responding to long-standing demands for statehood that were on the lines of ethnic or caste identities. Chhattisgarh, however, stands out for both the process of its creation and its subsequent developmental trajectory.

The movement for a separate Chhattisgarh had deep historical roots but gained momentum only in the 1990s. Earlier efforts in the 1950s and 1970s had failed to attract sustained political support, largely because the dominant parties in MP saw little advantage in reconfiguring administrative boundaries. By the 1990s, however, political and economic factors aligned in favor of statehood. The growing recognition that the southern and eastern districts of MP lagged significantly in development, combined with pressures for better administrative access to remote tribal regions, gave fresh impetus to the idea of a separate state. The decision by the Madhya Pradesh Legislative Assembly to endorse the reorganization in 1998, followed by parliamentary approval in 2000, made Chhattisgarh’s formation one of the least contentious state-splitting episodes in India’s history.

The bifurcation was driven more by elite consensus than by mass mobilization. Unlike Jharkhand or Uttarakhand, where statehood movements were marked by protest and ethnic mobilization, Chhattisgarh’s creation was negotiated quietly within mainstream political parties.<sup>7</sup> This elite-driven character would later influence the nature of the new state’s governance institutions—initially stable, relatively insulated from regional conflict, and closely aligned with national party structures. The resulting administrative handover was smooth: civil servants,

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<sup>7</sup> Refer to Tillin (2013), Tillin (2015), Heath and Tillin (2017), and Adhikari and Chhotray (2020) for more details on the creation of CH from MP.

infrastructure, and fiscal responsibilities were divided with minimal disruption, and the new state capital was established in Raipur with clear jurisdictional authority.<sup>8</sup>

The institutional context further supports this interpretation. Both states remained dominated by the same two major national parties—the Indian National Congress (INC) and the Bharatiya Janata Party (BJP). After 2003, the BJP held power continuously in both CH and MP, each under long-serving chief ministers (Raman Singh in CH and Shivraj Singh Chouhan in MP). Consequently, differences in political ideology, stability, or partisan alignment cannot explain the post-split divergence. Nor did the split coincide with large-scale fiscal transfers or natural-resource windfalls that could have favored CH relative to MP.

Instead, the reorganization fundamentally altered administrative geography and the relationship between the government and citizens.<sup>9</sup> Villages that became part of the new CH state were suddenly much closer to their capital, Raipur, than they had been to Bhopal. This reduction in administrative distance meant faster communication, shorter reporting chains, and more frequent oversight. In principle, such proximity could enhance state responsiveness and the monitoring of local bureaucrats. Whether it actually did so is the core empirical question our paper addresses.

In the next section, we describe the data and empirical design used to test this hypothesis. The identification strategy compares villages on either side of the new CH–MP border before and after 2000, focusing on outcomes most likely to respond to improvements in governance capacity and accountability.

### III. Research Design

#### *III.1. Data*

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<sup>8</sup> Upon creation, CH administration was accorded all powers that a ‘full’ state in India wields and independently exercised these powers over regions in the new state of CH. For example, the CH administration instituted various state agencies and undertakings, such as the Chhattisgarh State Industrial Investment Promotion Board, among others, upon creation. We provide more details on the powers granted in the online appendix.

<sup>9</sup> The CH-MP state-border was drawn in a way such that it coincided with the existing district boundaries at that time thus keeping the districts intact and their respective boundaries unchanged. This alleviates concerns about the endogeneity of new state border. We later show that villages close to and on either side of the CH-MP state-border were in fact largely similar in geography, climate, and other time-invariant characteristics.

We conduct our main analysis using data at the village-level (2001 Census boundaries) in CH and MP.<sup>10</sup> This section provides a description of the main variables, specifically satellite nighttime lights, firm-activity and non-farm employment, public goods provision, and efficiency of rural infrastructure program implementation, as well as their respective sources. Details on all variables used in this study are provided in the Online Appendix. Descriptive statistics of all variables used in this study are reported in Table 1.

#### *Satellite Nighttime Lights Data:*

The satellite nighttime lights data is processed and maintained by the Earth Observation Group (EOG) of the Payne Institute for Public Policy at Colorado School of Mines. Thus far, images of nighttime lights have been captured by two sensors, namely OLS onboard the DMSP satellites and VIIRS onboard the SNPP and NOAA-20 satellites. The DMSP nighttime lights dataset (v4) spans 1992 – 2013 while the VIIRS nighttime lights annual series (v2) spans 2012 – 2021. Differences in sensor technologies, spatial resolution, and dynamic range of the raw data captured by the two sensors respectively make the two datasets incompatible.<sup>11</sup> Li et al. (2020) generate a harmonized dataset spanning 1992 – 2018 by integrating the DMSP-OLS and VIIRS datasets. Due to differences in the sensitivity of OLS and VIIRS sensors, Li et al. (2020) caution users from applying their integrated dataset in rural areas for years after 2013. On comparing DMSP data and the simulated DMSP-like data from VIIRS for the year 2013, Li et al. (2020) find their integrated data to be discontinuous in rural areas (regions of low luminance) of Brazil. We find a similar pattern across villages (rural areas) in India (Table A1 in Online Appendix). Considering the incomparability across the two datasets beyond 2013, we primarily focus on the DMSP-OLS nighttime lights dataset and use its calibrated version by Li et al. (2020) which makes it comparable across years even though six different satellites are used.

This data is in the form of images of nighttime luminosity generated from the earth's surface. These nighttime lights images are composed of billions of pixels (scaled to a 30-arc-second grid or approx. 1 km<sup>2</sup>) and the luminosity generated from each pixel ranges from 0 – 63. Figure 2 showcases the nighttime lights image for CH and MP in 2000 (Panel A) (the year of the

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<sup>10</sup> All GIS data in this paper is extracted using the 2001 village-level shapefiles of CH and MP. All non-GIS village-level data is matched to the 2001 Census village-boundaries using SHRUG *keys* (Asher et al., 2021). Additional information on the shapefiles and SHRUG *keys* can be found in the Online Appendix.

<sup>11</sup> See Elvidge et al. (2013), Michalopoulos and Papaioannou (2018), and Li et al. (2020) for a detailed review of differences between DMSP-OLS and VIIRS nighttime lights data.

split) and 2013 (Panel B) (13 years after the split). One can see from the figure that the nighttime lights are brighter in CH in 2013 compared to 2000 but not much change is observed in the region that was in MP before and after the split.

Using tools in ArcGIS, we obtain a measure of *nighttime lights density* (nighttime lights per sq. km) by averaging across all pixels that fall within each village in a particular year.<sup>12</sup> It is important to note that a *nighttime lights density* value of zero for an inhabited village may not necessarily imply that the village emits zero luminosity or is completely dark. Presuming that an inhabited village, with some human population, emits some level of luminosity, the zero nighttime light emission in such a case is considered to be either due to the inability of the satellite to detect low levels of nighttime light emissions or a censoring problem, wherein the lowest non-zero values are filtered away and recoded to zero during the initial processing of the data by the NOAA. Considering this, we follow Henderson et al. (2018), Bruederle and Hodler (2018), and Michalopoulos and Papaioannou (2014) and limit our analysis to villages with records of inhabitation or human settlement (Census 2001). Another advantage of this strategy is that by focusing on inhabited villages, we indirectly exclude areas with dense forest cover, largely prevalent across MP and CH, specifically along certain segments of the CH-MP state-border on either side that may bias our results.

Following previous literature, we add a small constant of 0.01 before taking the natural log so as to not drop zero *nighttime lights density* observations from our analysis.<sup>13</sup> This log-transformed measure of nighttime lights density serves as a proxy for the level of economic development or income per capita for each village in a particular year.<sup>14</sup> We compute an average of this measure of nighttime lights density for each village for the pre-split (1993 – 2000) and post-

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<sup>12</sup> Additional details on the construction of nightlights density are provided in the Online Appendix.

<sup>13</sup> Our benchmark results with nighttime luminosity are robust to using other constants in the natural log transformation of nighttime lights density instead of 0.01 (see Table A7 in Online Appendix). Following Henderson et al. (2018), Bruederle and Hodler (2018), and Michalopoulos and Papaioannou (2014), we use 1 and 0.0029985 (smallest non-zero value of nighttime lights density) as constants in the natural log transformation and find our benchmark results to be highly robust.

<sup>14</sup> Many papers, including Jha and Talathi (2023, 2024), Pinkovskiy (2017), and Chanda and Kabiraj (2020) among others, use nighttime lights per capita instead of nighttime lights density. Since population data at village-level is limited to census years of 1991, 2001, and 2011, we focus on nighttime lights density following previous literature. This enables us to circumvent any interpolation issues in population data for the years in between. Nonetheless, in results not reported, we find that our main results remain qualitatively robust when we use nighttime lights per capita.

split period (2001 – 2013) respectively, which serves as the main dependent variable in our analysis.<sup>15,16</sup>

*Non-Agricultural Firm-Level Activity and Non-Farm Employment Data:*

We obtain data on measures of non-agricultural firm activity and non-farm employment at the village-level from the Economic Census of 1998 and 2013.<sup>17</sup> An advantage of this data is that it captures firm-level activity (number of total firms, number of private firms, number of government firms) and non-farm employment (total non-farm employment, manufacturing employment, and industrial employment) just before the bifurcation (1998), when CH was a part of MP, as well as 12 years after CH's creation (2013), giving sufficient time for the CH administration's industrial policies to take effect.

*Public Goods Data:*

We use village-level census data (1991, 2001, 2011) on public goods (amenities) to compute measures of public goods delivery in each village in a particular period.<sup>18</sup> More specifically, we use the change in proportion of villages that had a middle school, healthcare center<sup>19</sup>, telephone connection, and power for all purposes, as outcome variables for each village in the pre-split (1991 – 2001) and post-split period (2001 – 2011) respectively.

*Rural Infrastructure Program Implementation Efficiency Data:*

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<sup>15</sup> On examining the share of villages in India with zero nighttime lights density, we note that the change (drop) in this share is relatively more discontinuous from 1992 to 1993 compared to the change (drop) in this share in later years. Therefore, we use 1993 as the start year similar to Jha and Talathi (2023, 2024) who provide more information on the quality of the 1992 nighttime lights data. In result not reported, we find that our main results are highly robust when we perform our analysis using data for years spanning 1992 – 2013 instead of 1993 – 2013.

<sup>16</sup> Our benchmark results with nighttime lights are highly robust to an alternate form of the nighttime lights dependent variable wherein we use an indicator for whether a village, on average, is lit in the respective period as the dependent variable instead of the natural log of nighttime lights density (see Table A7 in Online Appendix). This indicator variable takes a value of 1 if the nighttime lights density of a village in a particular period is non-zero, on average, and a value of 0 if the nighttime lights density of a village in a particular period is zero, on average. This indicator essentially represents the probability that a village is, on average, lit in a particular period on average.

<sup>17</sup> While the Economic Census data is also available for years 1990 and 2005, the data for these years is, however, largely missing for CH villages in our sample. Out of the observations available for CH villages near the border for years 1998 and 2013, the 1990 and 2005 data is only available for 27% of these observations. Additional information on measures of firm activity constructed using the Economic Census Data can be found in the Online Appendix and Asher et al. (2021).

<sup>18</sup> Additional information on village-level census data on public goods can be found in the Online Appendix and Asher et al. (2021).

<sup>19</sup> In our analysis, a village is defined to have a healthcare center if it had either of the following: a maternity and child welfare center, a primary health center, primary health sub-center, or a dispensary.

We refer to village-level administrative data of the Pradhan Mantri Gram Sadak Yojana (PMGSY) or the Prime Minister’s Rural Road Construction Program, which was launched in 2000 with the objective of constructing paved (or *pucca*) roads in villages that did not have them<sup>20</sup>, for proxies related to the efficiency of rural infrastructure program implementation. Using administrative data of the PMGSY available at the village-level<sup>21</sup>, we construct two measures, specifically the natural log of average productivity (average rate of road construction) and the natural log of average cost efficiency (ratio of stipulated to actual cost) of road construction projects in a village between 2001 and 2015, to capture the state administration’s efficiency in implementing government programs.<sup>22</sup> One caveat of this data is that, since the PMGSY was launched in August 2000, the data is, therefore, only available from 2001 onwards i.e., the period after CH’s creation.

#### *Political Accountability Data:*

We measure political accountability using two indicators from the Trivedi Centre for Political Data (TCPD) (Asher et al., 2021; Jensenius and Verniers, 2017) – voter turnout as well as the inverse of winning margin (between winner and first runner-up) in state legislative elections held before (1985, 1990, 1993, 1998) and after the bifurcation (2003, 2008, 2013).<sup>23</sup>

In the following section, we discuss the methodology and empirical specification.

### *III.2. Methodology and Empirical Specification*

#### *III.2.1. Sample*

To causally identify the impact of state split, we compare villages on either side of the new CH-MP border before and after the split in a DiD and a DiDC framework. We construct two samples

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<sup>20</sup> In villages that had a dirt (or *kutchra*) road, the goal was to upgrade the preexisting roads (Asher and Novosad, 2020).

<sup>21</sup> The dataset contains administration information related to each road construction project in respective villages including the length (km) of road constructed under each project, time (days) taken to complete each project, and the actual and stipulated cost of each project among others. See Asher and Novosad (2020) and Lehne et al. (2018) for more information on the PMGSY administrative data.

<sup>22</sup> Following Asher and Novosad (2020), we primarily focus on villages that did not have a paved road in (or by) 2001 and where *new* road construction projects (under the PMGSY) were undertaken and implemented by the respective State administration between 2001 and 2015. Additional information on the PMGSY data and the construction of the two measures of state’s efficiency in implementing government programs can be found in the Online Appendix.

<sup>23</sup> Additional information on the source of State-legislative elections data as well as the construction of measures of accountability can be found in the Online Appendix.

– one for DiD and the other for DiDC – that allow comparison of villages on either side of the CH-MP state-border ( $b$ ) where pre-existing differences are likely to be minimal and pre-trends in economic activity are highly similar. We first identify districts adjacent to the CH-MP state-border, referred to as border districts ( $d$ ), as well as villages ( $v$ ) within each border district ( $d$ ). We then construct pairs ( $p$ ) of border districts ( $d$ ) that are contiguous and on either side of segment  $g$  of the CH-MP state-border ( $b$ ). The DiD sample consists of all villages within each border-district pair ( $p$ ) while the DiDC sample consists of villages within “X” km from the CH-MP border on either side. Considering that some forest covers (e.g., Dongargarh Khaara Reserve Forest)<sup>24</sup> extend as far as 25 km (geodesic distance) approximately from the CH-MP border into the respective state, we include villages that are an additional 25 km beyond the extent of the forest cover and use a bandwidth of 50 km in the DiDC analysis.<sup>25</sup>

We limit both analyses to *inhabited* villages on either side of the CH-MP state-border thus excluding areas with dense forest cover, largely prevalent across CH and MP, specifically along certain segments of the CH-MP state-border on either side that may bias our result.<sup>26</sup> Figure 2C shows the new state border in red and a yellow band around it is the area we focus on in our DiDC analysis. Figure 2D is a zoomed-in version of this border area.

### III.2.2. Empirical Specification

We estimate the DiD specification in equation (1) below.

$$y_{v,p,t} = \alpha_1 + \beta_1 \text{Newstate}_v + \text{Post}_t(\alpha_2 + \beta_2 \text{Newstate}_v) + \gamma_{pt} + \varepsilon_{v,p,t} \dots\dots(1)$$

$y_{v,p,t}$  is the outcome variable for village  $v$  within border-district pair  $p$  in period  $t$ .  $\text{Newstate}_v$  is an indicator for the treatment group which takes a value of 1 if a village eventually became a part

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<sup>24</sup> The Dongargarh Khaara Reserve Forest in Rajnandgaon district of CH is along the CH-MP border and extends almost 25 km (geodesic distance) into CH.

<sup>25</sup> Results are robust to a range of bandwidths between 30 km – 100 km. See Figures A1.A - A1.D in the Online Appendix in which we plot the DiDC estimates obtained for a range of bandwidths from 30 km – 100 km with log-transformed nighttime lights density (Figure A1.A), measures of firm-level activity and non-farm employment (Figure A2.A), public goods provision (Figure A1.C), and program implementation efficiency (Figure A1.D), as the outcome variables respectively.

<sup>26</sup> These forests, along certain segments of the CH-MP border, include the Balaghat Hill – Forest Range, Sanjay National Park, Dongargarh Khaara Reserve Forest, and Achanakmar Wildlife Sanctuary among others. MP (77,700 sq. km) and CH (55,674 sq. km) also account for the largest and third largest forest cover in India (by area) respectively. Refer to the State of Forest Report 2011 (Forest Survey of India, Ministry of Environment and Forests) for more information on forest covers in India.

of the *new* state of CH, and 0 otherwise.  $Post_t$  is an indicator for the period after the creation of CH which takes a value of 1 for the 2001 – 2013 period (post-split) and 0 for the 1993 – 2000 period (pre-split). It also accounts for any shocks before and after the bifurcation.  $\gamma_{pt}$  represents time-varying border-district pair fixed effects (or pair-period fixed effects) which allows comparison of villages within border-district pairs  $p$  over time-period  $t$  and accounts for any border-district as well as border-segment specific differences.<sup>27</sup> Note that a village  $v$  in border district  $d$  will appear  $m$  times in our sample if it is a part of  $m$  border district pairs ( $p$ ).

We augment the DiD specification in equation (1) with a first-order ( $q = 1$ ) RD polynomial and estimate the DiDC specification in equation (2) below for the DiDC sample.

$$y_{v,p,t} = \alpha_1 + \beta_1 Newstate_v + Post_t(\alpha_2 + \beta_2 Newstate_v) + f_t(D_v) + \gamma_{pt} + \varepsilon_{v,p,t} \dots\dots(2)$$

$f_t(D_v)$  in equation (2) represents the first-order ( $q = 1$ ) RD polynomial which is defined as follows.<sup>28</sup>

$$f_t(D_v) = \lambda_{1t} distance_v + \lambda_{2t} distance_v \times Newstate_v$$

Effectively, we use an interacted linear polynomial in distance to state-border in all estimations allowing separate linear trends in distance to state-border for each side in each period  $t$ . Note that,  $distance_v$  is positive for the CH side and negative for the MP side of the border.

$\beta_2$ , the coefficient on the interaction of  $Newstate_v$  and  $Post_t$  in the DiD and DiDC specifications respectively, is our coefficient of interest. A positive and significant  $\beta_2$  would imply that the creation of the new state had a positive effect on the economic development of CH villages close to the border (*treatment* group) relative to their counterparts across the border (*control* group). Standard errors are clustered at the subdistrict ( $i$ ) – district ( $d$ ) – pair ( $p$ ) level in both the estimations.<sup>29</sup>

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<sup>27</sup> We find that our main results are robust to the exclusion of border-district pair fixed effects ( $\gamma_p$ ) which we discuss later in section IV.1.

<sup>28</sup> See Imbens and Lemieux (2008) and Dell (2010). Our main results with nighttime lights, measures of firm-level activity and non-farm employment, delivery of public goods, and program implementation efficiency as outcome variables are highly robust to a single-dimensional, non-parametric (simple linear polynomial) and semiparametric (higher-order polynomial) RD approach (see Table A5 in Online Appendix) as well as a multi-dimensional, non-parametric and semiparametric RD approach (see Table A6 in Online Appendix). Additional information on RD polynomials of varying orders in single as well as multi-dimensions can be found in the Online Appendix and Dell (2010).

<sup>29</sup> See Abadie et al. (2023) and Asher et al. (2018). Since both of our samples include villages from approximately the same geographical location, spatial correlation is less of an issue in our analysis. However, for completeness, we compute Conley

In the next section, we discuss the main results of our study.

## IV. Main Results

### *IV.1. DiD results*

Panel A of Table 2 reports the baseline DiD estimates. We first obtain DiD estimates for a sample of all villages in CH and MP (column 1 of Panel A in Table 2) as per specification in equation (1) but without the pair-period fixed effects which are applicable only in the border samples. The estimate of  $\beta_2$  is large suggesting that the creation of the new state resulted in higher average level of nighttime lights in CH, by about 222 percentage points (pp), relative to their counterparts in MP.

The validity of this result, however, rests on the assumption of parallel trends. To test this assumption, we perform a falsification test using pre-treatment data (1993 – 2000) and replicate estimations in Panel A of Table 2 but assume that the creation of CH from MP occurred in 1996 (*placebo* split) instead of 2000. Results of this falsification test are reported in Panel B of Table 2. We find that the placebo DiD estimate in column 1 of Panel B is highly significant implying that the treatment and control groups in this sample were on differential trends in the pre-treatment period which makes the DiD design for this sample invalid and renders the DiD estimates in column 1 of Panel A biased. The violation of parallel trends in this sample could potentially be due to an array of reasons including long-standing differences in confounders such as geography, climate, initial economic conditions, resource endowments, and unobservable characteristics in pre-split period.

In light of these potential long-standing differences, we follow Chaurey (2017)'s most stringent specification and limit the sample to all villages within border-districts i.e., villages close to and on either side of the border. The motivation is that the regions on either side of the border are more likely to be similar as compared to geographically distant regions. This sample effectively

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standard errors (Conley, 1999) using the methodology developed by Colella et al. (2019) to account for spatial correlation. Following Burgess et al. (2018) and Asher et al. (2018), we additionally test for spatial correlation by clustering standard errors at the grid level (approx. 10 km  $\times$  10 km) as well as at the grid – district – pair level i.e., a higher level of spatial aggregation. We find our main results with nighttime lights, measures of firm-level activity and non-farm employment, delivery of public goods, and program implementation efficiency as outcome variables to be highly robust to both the exercises (see Tables A3 and A4 in Online Appendix).

enables us to compare like-to-like villages on either side of the new CH-MP border before and after the split and minimizes the likelihood of violating the parallel trends assumption.

The results using the sample of all villages within border-districts are reported in columns 2 and 3 of Table 2. Coefficients in column 2 are estimated without pair-period fixed effects while coefficients in column 3 are estimated with pair-period fixed effects as per the specification in equation (1).<sup>30</sup> The estimates of  $\beta_2$  in columns 2 and 3 (average local effect near the border) are both consistent with those in column 1 (average overall effect) in terms of direction and significance but smaller in magnitude. The average level of nighttime lights in the border areas of CH in the post-period are higher by about 154 – 182 pp relative to their counterparts on the other side of the border in MP. Using a relevant elasticity estimate<sup>31</sup> for the level of per capita income on nighttime lights density, this effect translates to a 34 – 40 pp higher average level of income per capita.

More importantly, the corresponding placebo DiD estimates in columns 2 and 3 of Panel B in Table 2 cease to be statistically significant indicating that treatment and control groups in this sample i.e., CH and MP villages close to and on either side of the border were on parallel trends in the pre-treatment period thus making the average local effect estimated in columns 2 and 3 of Panel A valid. We additionally confirm this by looking at trends in nighttime lights density of CH (treatment group) and MP villages (control group) in border-districts during the 1993 – 2013 period in Figure 3A.<sup>32</sup> We see that the trends in nighttime lights across the treatment and control groups are almost coinciding (or superimposed on top of one another) before the split (during 1993 – 2000), which confirms parallel trends across the two groups in the pre-treatment period, and that the two groups diverge significantly only after the split (during 2001 – 2013).

Next, we confirm the robustness of our valid DiD estimates in columns 2 and 3 of Panel A in Table 2 to an alternate empirical methodology – DiDC – which is a combination of regression discontinuity (RD) and DiD (Grembi et al., 2016).

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<sup>30</sup> Since we do not account for pair-period fixed effects in column 2 of Table 2, a village  $v$  in border district  $d$  thus appears *only once* in our sample. However, since we account for pair-period fixed effects in column 3 of Table 2, a village  $v$  in border district  $d$  will appear  $m$  times in our sample if it is a part of  $m$  border-district pairs ( $p$ ) as discussed previously. This is the reason for the different number of observations in columns 2 and 3.

<sup>31</sup> An elasticity estimate of 0.22 is used for level of per capita income with respect to nighttime lights density respectively. See Jha and Talathi (2024) and Henderson et al. (2012) for more information on these elasticity estimates.

<sup>32</sup> We plot the absolute nighttime light density instead of the log-transformed measure of nighttime lights density in Figure 3. In results not reported, we obtain similar trends on plotting the log-transformed measure of nighttime lights density.

#### IV.2. *DiDC Estimates*

Before delving into the corresponding DiDC estimates, we first examine discontinuities in the average level of nighttime lights density at the border in the pre-split and post-split period separately. For this, we group villages on either side of the border into 5 km bins and plot the mean of each bin up to 50 km on either side of the border for the pre-split and post-split period separately as depicted in Figure 4. We then plot a linear best fit line on each side which enables us to examine discontinuities at the border in each period.

We find that the average level of nighttime lights density across CH and MP villages was largely continuous at the border in the pre-split period i.e., the two groups within 50 km on either side of the border were balanced in terms of their average level of nighttime lights density. This is not surprising as the two groups were under the same administration before the bifurcation as well as in the same geographical vicinity and proximity from the state administration and so were likely to have similar levels of development. We additionally confirm that the two groups were also balanced in terms of their time-invariant characteristics such as geography, climate, area, and location in Figure 5.<sup>33</sup> We find no abrupt jumps at the border in these time-invariant characteristics across the two groups which also mitigates the concern that the CH-MP border was drawn along certain geographic divisions.

After the creation of CH, we observe a substantial discontinuity in the average level of nighttime lights density at the border as one crosses the border from MP into CH in Figure 4. Considering that the two groups were balanced in terms of their average level of nighttime lights density in the pre-split period as well as time-invariant characteristics, the abrupt jump in the average level of nighttime lights density at the border in the post-split period is indicative of the differential impact of responsive governance on economic development. The DiDC plot in the third column of Figure 4 is effectively the difference between the post-split RD plot and the pre-split RD plot.

We report the corresponding DiDC estimates in columns 4 and 5 of Panel A in Table 2. Coefficients in column 4 are estimated without pair-period fixed effects while coefficients in

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<sup>33</sup> We obtain RD estimates using the time-invariant characteristics, such as geography, climate, area, and location, as outcome variables and report the results in Table A2 in the Online Appendix. More information on the RD specification used to obtain these estimates can be found in the Online Appendix. Figure 5 contains the complementary RD plots of these estimates. Information on data used for geography, climate, area, and location can be found in the Online Appendix.

column 5 are estimated with pair-period fixed effects as per the specification in equation (2).<sup>34</sup> The average local effect at the border is estimated to be about 107 – 120 pp higher average level of nighttime lights density which translates to a 24 – 26 pp higher average level of income per capita for CH villages relative to their counterparts on the other side of the border.

The validity of the DiDC estimates rests on two main assumptions: *First*, there are (local) parallel trends close to the border before the split. Looking at the placebo DiDC estimates in columns 4 and 5 of Panel B of Table 2, we see that they are both close to zero and statistically insignificant which suggests that the two groups near the border were on (local) parallel trends in the period before the split. The trends in nighttime lights density of CH and MP villages within 50 km on either side of the border during the 1993 – 2013 period in Figure 3B further confirm that the two groups close to the border were, in fact, on parallel trends.

*Second*, there is no manipulative sorting of population across the CH-MP state-border. Our DiDC estimates may potentially be biased if people from MP villages near the border migrated into CH villages on the other side of the border after the split. Given that a large share of nighttime lights is human generated, significant migration from MP into CH would thus inflate luminosity levels emitted from CH regions thereby inducing an upward bias in our main results. Considering that spatial mobility in rural India is considerably low (Munshi and Rosenzweig, 2009) and people in villages are tied to their land, the probability of migration across CH-MP border seems small. Nonetheless, if there was any migration at all, it would be captured by the change in population density after the split.

We, therefore, examine the change in population density across CH and MP villages near the border before and after the split. Using village-level population density data from the Census of 1991, 2001, and 2011<sup>35</sup>, we compute the change in population density for periods 1991 – 2001 (pre-split) and 2001 – 2011 (post-split) and examine discontinuities in the change in population density before and after the split as well as the differences in these discontinuities and document the results graphically in Figure 6.<sup>36</sup> We find no abrupt jumps in the change in population density

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<sup>34</sup> Since we do not account for pair-period fixed effects in column 4 of Table 2, a village  $v$  in border district  $d$  thus appears *only once* in our sample. However, since we account for pair-period fixed effects in column 5 of Table 2, a village  $v$  in border district  $d$  will appear  $m$  times in our sample if it is a part of  $m$  border-district pairs ( $p$ ) as discussed previously. This is the reason for the different number of observations in columns 4 and 5.

<sup>35</sup> Additional information on village-level census data on population density can be found in the Online Appendix.

<sup>36</sup> Similar to Figure 4, we group villages on either side of the border into 5 km bins and plot the mean of each bin up to 50 km on either side of the border for the pre-split and post-split period separately. We then plot a linear best fit line on each side which enables us to examine discontinuities at the border in each period. The DiDC plot in the third column of Figure 6 is effectively the difference between the post-split RD plot and the pre-split RD plot.

across the CH-MP border before and after the split with the DiDC estimate being close-to-zero and insignificant. This confirms that there was no manipulative sorting of population across the CH-MP border and that our DiDC estimates are not biased by it. More importantly, this also rules out cross-border migration as a potential confounder and further strengthens our argument that the average local effect at the border is in fact driven by differences in responsive governance.

In sum, our main results are thus robust to the DiDC methodology including the most stringent specification in column 5 of Table 2 where we include pair-period fixed effects and compare villages within 50 km on either side of the border. In the remainder of the paper, we treat the DiD specification in column 3 of Panel A of Table 2 as well as the DiDC specification in column 5 of Panel A of Table 2 as our benchmark specifications respectively.

In addition to documenting the validity of our benchmark DiD and DiDC results with nighttime lights, we further address two commonly cited issues, specifically top-coding and overflow and blooming, in the nighttime lights data.<sup>37</sup> The nighttime lights data of Li et al. (2020) is top-coded (censored) at a DN of 63 which limits variation across the brightest areas. Since our analysis focuses on rural villages near the CH-MP border which emit low levels of nighttime luminosity as discussed previously, we do not consider top-coding to be a major concern in our analysis. Nonetheless, for completeness, we replicate our benchmark DiD and DiDC specifications using the nighttime lights data published by Zhao et al. (2022) who correct for top-coding as well as inter-annual inconsistency in nighttime lights data (Table A8 in the Online Appendix). We find our benchmark results to be highly robust to the use of Zhao et al. (2022) nighttime lights data.

The overflow and blooming phenomenon pertains to the spillover of nighttime luminosity from its origin into neighboring regions. Since we focus on villages in adjacent districts across the CH-MP border, this problem is likely to prevail in our analysis. As a result of the spillover, light from the faster-growing or more developed side would thus illuminate the slower-growing or less developed side making it appear to be growing faster or more developed than it really is (Pinkovskiy, 2017). Such a spillover of nighttime luminosity, if any, would tend to make neighboring regions more similarly lit thus acting against our benchmark results. We check this by performing a “donut exercise” wherein we exclude villages within 5 km from the CH-MP border on either side to account for overflow and blooming in the nighttime lights data

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<sup>37</sup> See Henderson et al. (2012), Chanda and Kabiraj (2020) for more information on top-coding and overflow and blooming issue in nighttime lights data.

(Michalopoulos and Papaionnou, 2014) (Table A8 in the Online Appendix). We find that the resulting DiD and DiDC estimates of the “donut exercise” are larger in magnitude compared to our benchmark estimates thus confirming the prevalence of the overflow and blooming phenomenon of nighttime lights in our benchmark analysis and indicates that our benchmark results with nighttime lights are lower-bound estimates.

Overall, the results indicate that transferring administrative control to a new state government had a large and persistent positive impact on local economic development. In the following section, we investigate the effect on some additional indicators of development, specifically firm-level activity and non-farm employment, delivery of public goods, and efficiency of government program implementation.

### *IV.3. Effect on Additional Indicators of Development at the Border*

#### *IV.3.1. Non-Agricultural Firm-Level Activity and Non-Farm Employment*

Since the economic trajectory of CH primarily took off after the transfer of power and autonomy to the new and independent CH administration owing to its creation in 2000, one plausible explanation could be that CH’s economic policies were more target-centric, focused, and effective in driving economic development relative to the MP administration. We investigate this in the context of CH’s ambitious industrial policies that were adopted by successive governments after its creation.

Between 2001 and 2014, a total of three industrial policies, spanning 2001 – 2003, 2004 – 2009, and 2009 – 2014, were adopted by successive CH governments since its creation. A common objective of these policies was to add maximum value to the state’s abundant natural resources and create maximum employment opportunities by setting up industries, primarily driven by private sector participation, all over the state which would ultimately promote growth and development of the region. The policies endeavored to achieve this by ensuring availability and provision of basic industrial infrastructure (e.g., power<sup>38</sup>), establishing an efficient system<sup>39</sup> of

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<sup>38</sup> CH administration provided special incentives for captive power generation and directed the CH State Electricity Board to ensure uninterrupted supply of quality power to industries.

<sup>39</sup> This included the construction of an administrative complex in the State capital (Raipur) that would house all departments/agencies associated with industrial investment promotion, the constitution of a State Level Industry Advisory Board that came directly under the purview of the Chief Minister for regular consultations, strengthening of the District Investment

“*single point contact*” and “*time bound clearance*” that facilitated all statutory and administrative clearances for investment and provided necessary facilities and services in a hassle-free manner, providing special directed incentives<sup>40</sup> for industrial investment (e.g., capital investment and interest subsidies, exemption from entry tax, etc.), and encouraging technology upgradation, patent registration, R&D, foreign direct investment as well as investment by non-resident Indians through additional financial incentives.<sup>41</sup>

But how are CH’s effective industrial policies relevant in our analysis? Recent literature has documented a strong causal link between nighttime light emission and firm-level activity (Bilicka and Seidel, 2022, Mellander et al., 2015). This relationship is found to be primarily driven by light emitted from firm’s fixed infrastructure, production activities (e.g., use of labor), and construction of new firms among other firm activities. Recent work has also validated the use of nighttime lights as a proxy for non-farm employment (e.g., manufacturing employment) (Asher et al., 2021). Considering these findings, if we find evidence of a larger increase in firm-level activity and non-farm employment in CH villages near the border relative to their counterparts on the other side, one can then argue that the main results, in part, are driven by the effectiveness of CH’s industrial policies.

We empirically investigate this by examining the growth in the number of firms, specifically private firms, as well as non-farm employment. We estimate our benchmark DiD and DiDC specifications using measures of firm-level activity (number of total firms, number of private firms, number of government firms) and non-farm employment (total non-farm employment, manufacturing employment, and industrial employment) as outcome variables and report the respective estimates from this analysis in columns 1 – 6 of Table 3. Panel A reports the coefficients estimated using the benchmark DiD specification while Panel B reports coefficients estimated using the benchmark DiDC specification. We find that there was a larger increase in the number of firms in CH villages near the border relative to their counterparts on the other side in MP. Examining estimates in columns 1 – 3, we learn that this was driven primarily by the larger

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Promotion Committees and the State Industrial Promotion Board that were created under the CH Industrial Investment Promotion Act, 2002, and taking necessary measures to simplify labor laws.

<sup>40</sup> These included interest and capital investment subsidies, exemption from duties such as electricity duty, stamp duty, and entry tax, exemption from land diversion fee, allotment of plots at concessional premium in industrial areas, quality certification subsidies, and technology patent subsidies among others.

<sup>41</sup> The State Industrial Investment Promotion Board along with its cross-functional committee was given the responsibility of monitoring the implementation of the industrial policies. More information on the CH’s Industrial Policies can be found on the CH State Government’s website (Accessed on Sep 10, 2023).

increase in the number of private sector firms in CH villages under the new CH administration after its creation. We also find evidence of a larger increase in overall non-farm employment as well as manufacturing and industrial employment<sup>42</sup> in CH villages near the border relative to MP villages on the other side of the border (columns 4 – 6).

Since we only have data for one year (1998) before the split, we are unable to validate the parallel trends assumption in this case. Nonetheless, the coefficient on *Newstate<sub>v</sub>* is negative in columns 1 – 6 which indicates that the CH side of the border had a smaller number of firms (private) as well as lower non-farm employment relative to the MP side of the border when the two sides were under the same administration in the pre-split period. Since the pre-split data is for 1998, which was just 2 years before the split, the larger increase in the number of private sector firms and overall non-farm employment from 1998 to 2013 is likely to be a result of improved governance exhibited by the new CH administration in the post-split period in implementing its ambitious industrial policies.<sup>43</sup>

#### *IV.3.2. Delivery of Public Goods*

Provision of public goods is known to be an important determinant of economic development. Since responsibilities and powers over various matters including the provision of public goods for the CH region were transferred to the CH administration after CH's creation, it is plausible that there was an improvement in the delivery of public goods in CH villages under the new administration, relative to when they were under the MP administration before the bifurcation, which would be consistent with the other results discussed previously. In light of previous studies that document a significant positive relationship between public goods and nighttime lights<sup>44</sup>, we investigate this conjecture empirically by estimating our benchmark DiD and DiDC specifications using measures of public goods provision at village-level, specifically the change in proportion of villages that had a middle school, healthcare center, telephone connection, and power for all

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<sup>42</sup> Industrial employment is the summation of employment in manufacturing (registered and unregistered), construction, electricity, gas, and water supply, and mining and quarrying sectors.

<sup>43</sup> We also see a growth in manufacturing and industrial employment on the CH side, from the pre-split to the post-split period, relative to the MP side of the border. Specifically, we find the CH side closing in on the difference from the pre-split to the post-split period and having caught up with the MP side in the post-split period.

<sup>44</sup> See Asher et al. (2021), Billing (2019), Shenoy (2018).

purposes, as outcome variables and report our findings in columns 7 – 10 of Table 3.<sup>45</sup> Panel A reports the coefficients estimated using the benchmark DiD specification while Panel B reports coefficients estimated using the benchmark DiDC specification. We find a relatively larger increase in the proportion of CH villages, near the border, that had a school, healthcare center, telephone connection, and power (for all purposes) under the *new* CH administration compared to when they were under the MP administration before the bifurcation.

Since we use the change in proportion of villages that had the respective public good, the coefficient on *Newstate<sub>v</sub>* in these regressions effectively provides information on the pre-trends across the two groups on either side of the border. With respect to schools, we see that the two groups had differential trends in the pre-split period in the DiD specification that is based on a sample of villages within border-districts. The location of these villages spans approx. 130 – 160 km from the border on either side. As we limit the sample to villages within 50 km from the border on either side in the DiDC specification, we see that the coefficient on *Newstate<sub>v</sub>* is no longer significant suggesting that parallel trends in the pre-split period hold closer to the border for schools. In the case of healthcare centers, we see that villages on the CH side had a downward trend relative to villages on the MP side in the pre-split period i.e., the two groups were on differential trends. Nevertheless, we find that CH villages had a larger increase in proportion of villages with a healthcare center suggesting that not only did CH villages catch-up but the improvement in the provision of healthcare centers was above and beyond relative to that in MP villages. Looking at telephone connections and power (for all purposes), we see that the two groups were largely on parallel trends in the pre-split period.<sup>46</sup>

Overall, we find sufficient evidence to rule out the possibility that the larger improvement in the delivery of public goods on the CH side is driven by increasing pre-trends. Considering the stringency of our specification, the larger increase in the proportion of villages with schools, healthcare centers, telephone connections, and power (for all purposes) on the CH side is, therefore, likely to be a result of the bifurcation that enabled the new CH to provide more accountable and responsive governance.

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<sup>45</sup> The change between 1991 and 2001 captures the period before the split while the change between 2001 and 2011 captures the period after the split.

<sup>46</sup> In the case of power (for all purposes), we find weak evidence of the two groups being on differential trends in the pre-split period in the DiDC specification when we limit the sample to villages within 50 km from the border on either side. However, as we include all villages in border-districts that are up to approximately 130 – 160 km from the border on either side, we see that parallel trends in the pre-split period hold.

### *IV.3.3. Efficient Implementation of Government Programs*

State's ability to implement government programs efficiently is more direct evidence of more accountable and responsive governance. The transfer of control and autonomy over the CH region to a new state administration upon CH's creation also meant that the new administration was responsible for the implementation of government programs in the CH region. We investigate this in the context of a flagship rural roads construction program – PMGSY – wherein the responsibility of implementing the PMGSY was delegated to State governments.

Since the PMGSY was launched in August 2000, this analysis can only be done for the post-split period. Using the average productivity and average cost efficiency of road construction projects in a village between 2001 and 2015 as outcome variables<sup>47</sup>, we estimate a simple OLS specification in place of our benchmark DiD specification and a RD specification in place of our benchmark DiDC specification and report our findings in columns 11 – 12 of Table 3.<sup>48</sup> Panel A reports the coefficients estimated using the OLS specification while Panel B reports coefficients estimated using the RD specification.

We find that average productivity and cost efficiency of new road construction projects was higher under the new CH administration relative to the MP administration. Since the PMGSY was launched close to CH's creation in 2000, one caveat of this analysis is that we are not able to determine how the two groups would have otherwise performed when they were both under the MP administration in the pre-split period, nevertheless, it is consistent with evidence of more responsive governance in CH.

The results point to a consistent conclusion: the creation of Chhattisgarh produced measurable economic gains for areas that came under the new state administration. Because political ideology, party control, and broader macroeconomic conditions were common to both sides of the border, the most plausible channel is improved governance arising from administrative proximity. Villages that became part of CH were suddenly within a shorter distance from the capital which facilitated communication, increased oversight visits, and gave local officials and

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<sup>47</sup> We use the natural log of the two measures, specifically average productivity and cost efficiency, in our estimations.

<sup>48</sup> More information on the OLS and RD specifications used in these estimations respectively is provided in the Online Appendix.

citizens easier access to decision-makers. Over time, this proximity likely strengthened accountability relationships and improved implementation capacity.

The next section probes these mechanisms directly, focusing on administrative distance and electoral competitiveness as channels through which decentralization influenced outcomes.

## V. Mechanisms: Administrative Proximity and Political Accountability

### V.1. Proximity to State Capital (Administration)

The most immediate effect of statehood was a dramatic change in administrative geography. Before 2000, border villages (in CH region) were governed from Bhopal—roughly 450–480 kilometers away. After the split, the same villages were now only 130–150 kilometers from Raipur, the new capital of CH. This nearly threefold reduction in distance implied a fundamental shift in how local governments interacted with higher-level authorities. We quantify this mechanism using the distance to the state capital as a continuous treatment variable within the DiD and DiDC frameworks.

Using the geodesic distance (unit of 100 km),  $DistCap_v$ , between village centroids and their respective state capitals (CH – Raipur; MP – Bhopal), we augment our benchmark DiD and DiDC specifications in equations (1) and (2) with  $DistCap_v$ ,  $Newstate_v \times DistCap_v$ ,  $Post_t \times DistCap_v$ , and  $Newstate_v \times Post_t \times DistCap_v$  and estimate the augmented specification in equation (3).

$$y_{v,p,t} = \alpha_1 + \beta_1 Newstate_v + \beta_2 DistCap_v + \beta_3 Newstate_v \times DistCap_v + Post_t (\alpha_2 + \beta_4 Newstate_v + \beta_5 DistCap_v + \beta_6 Newstate_v \times DistCap_v) + f_t(D_v)I + \gamma_{pt} + \varepsilon_{v,p,t} \dots(3)$$

In equation (3),  $I$  is an indicator which takes the value 0 in the DiD case and 1 in the DiDC case.  $\beta_3$  and  $\beta_3 + \beta_6$  represent the differential impact of proximity to state capital on the dependent variable in the pre-split and post-split periods, respectively. Since Raipur only became the capital of CH in the post-split period, if “coming closer” to the state administration (Raipur) had any effect on development, we would expect the difference in impact of proximity to state capital on the

dependent variable between the post-split and pre-split period i.e.,  $\beta_6$  to be negative and highly significant.

We report estimates of the augmented DiD and DiDC specifications in columns 1 – 2 of Table 4 respectively. The estimates of  $\beta_6$  in the two columns are found to be negative, highly significant, and substantially large, ranging from -1.124 to -1.510, which suggests that “being closer” to its people is one reason why CH administration was able to deliver responsive governance.<sup>49</sup>

We additionally confirm that this is, in fact, a result of proximity to the state capital of Raipur in the post-split period rather than being an artifact of proximity to the major city of Raipur. We perform a falsification test, similar to the one in Table 2, using pre-treatment data (1993 – 2000) and assuming that the split occurred in 1996 (placebo split) instead of 2000. We report the corresponding placebo estimates of specifications in columns 1 – 2 of Table 4 in columns 3 – 4 of Table 4 respectively. While both the placebo estimates of  $\beta_6$  in columns 3 – 4 are negative, only the placebo  $\beta_6$  estimate in column 4 is significant. This broadly suggests that proximity to Raipur had a positive effect on development levels in CH villages near the border compared to their counterparts on the other side even in the pre-split period, when Raipur was only an emerging major city and not a capital of a state. This effect is, however, relatively much smaller in absolute magnitude when compared to that in columns 1 – 2. This difference in the magnitude of the placebo and main effect of proximity to Raipur effectively demonstrates the difference in proximity to just a major city versus proximity to the capital of a state.

We further corroborate this mechanism by replicating specifications in columns 1 – 2 of Table 4 with the additional indicators of development (from Table 3) as outcome variables in Table 5. The structure of Table 5 is similar to that of Table 3 wherein DiD (and OLS) estimates are reported in Panel A and DiDC (and RD) estimates are reported in Panel B.<sup>50</sup> While the coefficient of interest on the respective interaction term is found to be negative in all columns of both panels except for healthcare center, telephone, power (for all purposes), and cost efficiency of program implementation, it varies in its statistical significance across the two panels. Among the outcomes

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<sup>49</sup> This finding is consistent with a large body of literature that documents various consequences of the limited penetration and reach of the state in regions physically more distant from it such as decay in law enforcement (Michalopoulos and Papaioannou, 2014), misgovernance (Campante et al., 2019), greater levels of corruption (Campante and Do, 2014), irregular monitoring of infrastructure quality (Asher et al., 2018), and lower nighttime lights (Provenzano, 2024) among others.

<sup>50</sup> We augment the respective OLS and RD specifications with  $DistCap_v$  and  $Newstate_v \times DistCap_v$ . The coefficient on the interaction term  $Newstate_v \times DistCap_v$  is our coefficient of interest in this exercise.

for which we find a negative coefficient, it is significant for total number of firms, total number of private firms, manufacturing employment, industrial employment, schools, and productivity of program implementation in the DiD (and OLS) specifications while the negative coefficient is only significant for total number of government firms and schools in the DiDC (and RD) specifications. The difference in the statistical significance across the two specifications could be due to a variety of reasons including poor quality and measurement errors in the respective survey data as well as differences in the samples used in the two specifications. Nonetheless, the negative sign on the respective interaction terms in almost all columns is consistent with our results in Table 4.

Taken together, the evidence demonstrates that reduced administrative distance translated into improvements in indicators of development. This likely happened because, among other things, the monitoring of bureaucrats in district and block headquarters by higher officials became easier. Next, we argue that proximity as well as the inclusion of lower-caste elites in the state building process increased the accountability of local leaders to their constituents resulting in improved governance.

## *V.2. Electoral Competition and Local Accountability*

It has been argued that proximity to state administration promotes participation of local leaders in the state building process, gives them a voice in governance decisions, and increases their knowledge about the local conditions and constituent preferences (Gottlieb et al., 2016). Simultaneously, it also increases the residents' knowledge about the local administration's performance and makes it easier for the residents to make their demands heard as well as penalize their leaders electorally upon failure of their leaders to adequately address their demands (Tommasi and Weinschelbaum, 2007). Considering this, proximity can increase accountability and responsiveness of local leaders which, in turn, incentivizes them to address local disputes and concerns and develop effective and targeted policies.

We measure political accountability using two indicators – voter turnout and the inverse of win margin in state legislative elections.<sup>51,52</sup> A higher voter turnout and inverse of the win margin

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<sup>51</sup> Inverse of the win margin =  $1 - \text{win margin}$ , where win margin is the difference in vote shares of the winner and runner-up in State-legislative elections.

<sup>52</sup> See Besley and Burgess (2002), Jha and Talathi (2024), Ardanaz et al. (2014) for usage of similar variables to measure accountability.

imply higher participation and competitiveness in state-legislative elections respectively. A high degree of participation and competitiveness in the democratic process instills the fear of being replaced amongst incumbent local leaders and thus incentivizes them to be more responsive and accountable to their constituents.

We examine the pattern in political accountability before and after the bifurcation in a DiD setup described in equation (4).

$$y_{c,s,t} = \alpha_0 + \alpha_1 Newstate_c + Post_t(\alpha_2 + \alpha_3 Newstate_c) + \varepsilon_{c,s,t} \dots\dots\dots(4)$$

$y_{c,s,t}$  in equation (4) represents the outcome variable measuring political accountability in state-legislative assembly constituency  $c$  in state  $s$  in election year  $t$ .  $Newstate_c$  is an indicator for the treatment group which takes a value of 1 if a constituency  $c$  eventually became a part of the *new* state of CH, and 0 otherwise.  $\alpha_3$  in equation (4) represents the DiD estimate.<sup>53</sup> Standard errors are clustered at the district level in this estimation. Depending on the outcome variable, a positive and significant  $\alpha_3$  would imply that the bifurcation increased participation and/or competitiveness, on average, in state-legislative elections in CH compared to MP.

DiD estimates based on the specification in equation (4) are reported in columns 1 and 2 of Table 6. They show that bifurcation resulted in a larger increase in the average participation and competitiveness in local state-legislative elections in CH relative to MP. To ensure that our DiD estimates are not biased by omitted variables, we perform a like-to-like comparison, as per specification in equation (5) below, by focusing on state-legislative assembly constituencies in border-districts on either side of the CH-MP state-border.<sup>54</sup> These constituencies are likely to be similar in geography, climate, development, and other unobservable characteristics.

$$y_{c,p,t} = \alpha_0 + \alpha_1 Newstate_c + Post_t(\alpha_2 + \alpha_3 Newstate_c) + \gamma_{pt} + \varepsilon_{c,p,t} \dots\dots\dots(5)$$

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<sup>53</sup> On account of changes in state-legislative constituency boundaries after the delimitation in 2008, we do not account for constituency fixed effects.

<sup>54</sup> On account of the small number of constituencies in border-districts on either side of the CH-MP state-border, we only study this using the DiD estimator as opposed to using both – DiD and DiDC – estimators as done in all the previous discussions of the paper so far.

Similar to our benchmark DiD and DiDC estimations,  $\gamma_{pt}$  represents time-varying border-district pair fixed effects. DiD estimates based on specification in equation (5) are reported in columns 3 and 4 of Table 6. Standard errors are clustered at the district ( $d$ ) – pair ( $p$ ) level in this estimation.

While we do not see any effect of CH’s creation on the voter participation in these estimations, the effect on competitiveness in elections remains positive and highly significant and is in fact higher in magnitude. We additionally check the validity of these estimates by performing falsification (placebo) tests using data on elections held in the period before the bifurcation and assuming that the bifurcation happened in 1993 (placebo split) instead of 2000 (Table A9 in Online Appendix). We find that the parallel trends assumption holds for competitiveness in elections for both samples (all CH-MP constituencies as well as constituencies in border-districts) but not for participation in elections. This suggests that results on voter turnout should be interpreted with caution<sup>55</sup> and that focus should be on the election competitiveness measure which satisfies the parallel trends assumptions. Higher competitiveness in elections indicates how politicians had to work harder to win which aligns with the accountability narrative.

These findings align with qualitative accounts of political change in CH. As Tillin (2013) documents, the creation of the state enabled the rise of a new cadre of regional politicians drawn from lower-caste and tribal backgrounds. Many of these leaders had stronger local roots and faced greater expectations from their constituents. The combination of geographic proximity to the capital and a more competitive political environment thus created a virtuous cycle of accountability and performance.

Below we provide some concluding remarks.

## VI. Concluding Remarks

This paper shows how a transfer of regional control and autonomy can reshape development outcomes by altering proximity to power and political accountability. Using the creation of Chhattisgarh from Madhya Pradesh in 2000 as a natural experiment, we document that CH villages just inside the new state border experienced faster growth in nighttime lights, private enterprise,

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<sup>55</sup> One potential reason for differential pre-trends in voter turnout could be that individuals or groups may have changed their voting behavior in anticipation of the bifurcation in the pre-split period. This seems plausible, especially given that the resolution with respect to MP’s bifurcation was passed as early as the 1970s and was subsequently followed by a change in the political climate in the state during the 1980s and 1990s that ultimately led to the bifurcation in 2000 (Tillin, 2013).

public goods provision, and infrastructure delivery than otherwise similar villages in MP. These gains reflect more responsive and effective governance rather than differences in political stability, party ideology, migration, or pre-existing differences in economic trends.

We identify two central mechanisms. First, the bifurcation dramatically reduced the distance between CH villages near the border and their state capital, Raipur, bringing the state apparatus tangibly closer to citizens. Second, the formation of the new state altered political incentives: electoral competition in state legislative elections intensified more in CH than in MP, indicating that local leaders faced stronger pressure to perform. Together, these changes improved the alignment between state institutions and local needs.

Our findings contribute to broader debates on decentralization and state capacity. They highlight that institutional form alone is not enough: the spatial organization of the state—its administrative geography and the physical distance between citizens and decision-makers—can be as important as formal rules in shaping economic performance. They also suggest that decentralization is more likely to yield developmental gains when political institutions generate real electoral accountability and when new administrative units are given sufficient capacity and autonomy to act.

At the same time, the Chhattisgarh case has features that may have favored success: relatively low conflict around statehood, continuity in party systems, and stable leadership. Whether similar gains would arise in more fragmented or polarized settings remains an open question. Future research could examine how the effects of decentralization depend on the broader political environment, on the design of administrative units, and on the long-run evolution of accountability mechanisms once the initial “proximity shock” dissipates.

More generally, our results underscore that decisions about where to locate political authority and how to draw administrative boundaries have lasting economic consequences. In contexts where citizens remain physically and politically remote from state institutions, bringing government “closer to the people” may be a powerful—though not automatic—lever for improving development outcomes.

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**Table 1: Descriptive Statistics of Main Variables**

Variables	Pre-Split						Post-Split					
	Control Group			Treatment Group			Control Group			Treatment Group		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Avg. Nighttime Lights Density (Natural Log)	11,488	-3.089	2.236	8,982	-2.910	2.087	11,488	-2.988	2.247	8,982	-0.947	2.520
No. of Firms (All)	8,854	19.460	70.933	4,791	14.957	49.929	8,854	21.261	82.243	4,791	28.338	97.269
No. of Firms (Pvt)	8,854	17.184	68.674	4,791	12.579	44.872	8,854	18.609	78.625	4,791	24.934	92.011
No. of Firms (Gov)	8,854	2.275	3.223	4,791	2.378	5.897	8,854	2.652	4.807	4,791	3.405	6.389
Non-Farm Employment	8,854	37.132	166.206	4,791	28.768	117.590	8,854	40.559	187.162	4,791	66.837	367.477
Manufacturing Employment	8,854	13.765	58.309	4,791	8.343	29.875	8,854	7.685	34.110	4,791	8.723	51.555
Industrial Employment	8,854	14.558	61.837	4,791	9.257	35.531	8,854	8.827	42.182	4,791	10.561	62.733
Growth in Prop. Villages with a Middle School	3,904	0.002	0.208	1,756	-0.005	0.137	3,904	0.043	0.346	1,756	0.089	0.303
Growth in Prop. Villages with a Healthcare Center	10,732	0.198	0.418	5,110	0.059	0.280	10,732	-0.103	0.423	5,110	0.134	0.412
Growth in Prop. Villages with a Telephone Connection	10,888	0.087	0.306	5,249	0.080	0.278	10,888	0.066	0.399	5,249	0.137	0.395
Growth in Prop. Villages that have Power (all purposes)	3,776	0.858	0.351	1,420	0.878	0.329	3,776	-0.388	0.488	1,420	-0.096	0.301
Avg. Productivity of Road Const. Projects (Natural Log)	-	-	-	-	-	-	2,292	-4.852	0.761	2,583	-4.739	0.834
Avg. Cost Eff. of Road Const. Projects (Natural Log)	-	-	-	-	-	-	2,292	0.062	0.212	2,583	0.116	0.243
Distance to State-Capital (100 km)	11,488	4.057	0.713	8,982	4.806	0.653	11,488	4.057	0.713	8,982	1.518	0.812
Avg. Voter Turnout Ratio (All)	914	0.555	0.102	356	0.533	0.122	689	0.701	0.072	269	0.732	0.087
Avg. Voter Turnout Ratio (Border)	192	0.526	0.146	180	0.528	0.094	138	0.719	0.067	133	0.733	0.066
Avg. Inverse Win Margin (All)	914	0.869	0.110	356	0.856	0.131	689	0.885	0.089	269	0.905	0.076
Avg. Inverse Win Margin (Border)	192	0.878	0.105	180	0.858	0.130	138	0.888	0.085	133	0.913	0.091

*Notes* : Descriptive statistics for all variables, except Avg. Voter Turnout Ratio and Avg. Inverse Win Margin, are for a sample of villages that are within border-districts along the CH-MP state-border. Descriptive statistics for Avg. Voter Turnout Ratio and Avg. Inverse Win Margin are provided for two samples: 1.) state-legislative elections held in all CH-MP constituencies; 2.) state-legislative elections held in constituencies within border-districts along the CH-MP border. For Avg. Nighttime Lights Density (Natural Log) and Distance to State-Capital (100 km), the Pre-Split period spans 1993 - 2000 and the Post-Split period spans 2001 - 2013. For No. of Firms (All, Pvt, Gov) and Non-Farm Employment (All, Mfg., Indus.), the Pre-Split data is from Economic Census of 1998 and the Post-Split data is from Economic Census of 2013. For Growth in Prop. Villages with Public Goods (Middle School, Healthcare Center, Telephone Connection, Power), the Pre-Split period spans 1991 - 2001 and the Post-Split period spans 2001 - 2011. Measures of state administration's efficiency in implementing government programs (PMGSY), specifically the natural log of average productivity and the natural log of average cost efficiency of road construction projects, represent the average between 2001 and 2015. Avg. Voter Turnout Ratio and Avg. Inverse Win Margin are both computed using data from state-legislative elections held in 1985, 1990, 1993, and 1998 for the Pre-Split period and using data from state-legislative elections held in 2003, 2008, and 2013 for the Post-Split period.

**Table 2: Baseline Estimates of the Effect on Nighttime Lights Density**

Sample:	DiD			DiDC	
	All Villages	All Villages in Border-Districts	All Villages in Border-Districts	Villages within 50km from Border	Villages within 50km from Border
	(1)	(2)	(3)	(4)	(5)
Panel A: Actual Split in 2000					
Dep. Var: Avg. Level of Lights Density					
Newstate	-1.467*** (0.211)	0.147 (0.329)	0.153 (0.254)	-0.340 (0.467)	-0.180 (0.332)
Newstate × Post	2.220*** (0.136)	1.539*** (0.251)	1.824*** (0.163)	1.196** (0.457)	1.071*** (0.292)
Observations	131,722	23,832	40,940	13,056	24,942
Pair-Period FEs	NO	NO	YES	NO	YES
Panel B: Placebo Split in 1996					
Dep. Var: Avg. Level of Lights Density					
Newstate	-1.534*** (0.206)	0.202 (0.304)	0.204 (0.239)	-0.301 (0.412)	-0.152 (0.294)
Newstate × Post	0.134** (0.0547)	-0.111 (0.0932)	-0.101 (0.0772)	-0.0783 (0.167)	-0.0555 (0.133)
Observations	131,722	23,832	40,940	13,056	24,942
Pair-Period FEs	NO	NO	YES	NO	YES

*Notes*: Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. In Panel A (actual split in 2000), the Pre-Split period spans 1993 - 2000 and the Post-Split period spans 2001 - 2013. In Panel B (placebo split in 1996), the Pre-Split period spans 1993 - 1996 and the Post-Split period spans 1997 - 2000. Specifications in both panels use the average level of nighttime lights density as the outcome variable. DiD estimates are reported in columns 1 - 3 while DiDC estimates are reported in columns 4 - 5. Estimates in column 1 are based on a sample of all CH and MP villages, estimates in columns 2 - 3 are based on a sample of all CH and MP villages in border districts, and estimates in columns 4 - 5 are based on a sample of villages within 50 km from the CH-MP border.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 3: Effect on Additional Correlates of Economic Development**

Outcome:	Firm-Level Activity and Non-Farm Employment						Delivery of Public Goods				Implementation Efficiency	
	Firms (All)	Firms (Pvt)	Firms (Gov)	Non-Farm Emp.	Mfg. Emp.	Ind. Emp.	Schools	Health Cntr.	Telephone	Power	Productivity	Cost Efficiency
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Sample - All Villages in Border-Districts												
	DiD										OLS	
Newstate	-6.419*	-6.547*	0.127	-12.31	-7.567**	-7.496**	-0.0130**	-0.0885***	-0.0121	0.0436	0.144**	0.0470***
	(3.695)	(3.513)	(0.330)	(8.155)	(3.123)	(3.424)	(0.00600)	(0.0262)	(0.0209)	(0.0290)	(0.0646)	(0.0148)
Newstate × Post	13.66***	12.94***	0.715**	40.69***	7.480***	8.412***	0.0729***	0.279***	0.0693**	0.190**		
	(2.865)	(2.723)	(0.307)	(8.156)	(1.766)	(1.805)	(0.0188)	(0.0477)	(0.0282)	(0.0766)		
Observations	27,290	27,290	27,290	27,290	27,290	27,290	11,320	31,684	32,274	10,392	4,875	4,875
Panel B: Sample - Villages within 50 km from Border												
	DiDC										RD	
Newstate	-9.996***	-9.098***	-0.897**	-17.75**	-4.672**	-5.673**	0.0138	-0.170***	-0.0432	0.170*	0.319**	0.0784***
	(3.161)	(2.989)	(0.347)	(6.873)	(1.919)	(2.225)	(0.0130)	(0.0607)	(0.0352)	(0.0917)	(0.140)	(0.0263)
Newstate × Post	36.71**	36.56**	0.147	98.52***	4.016**	5.781**	0.117***	0.378***	0.0953	0.187		
	(14.12)	(13.77)	(0.661)	(36.69)	(2.004)	(2.480)	(0.0427)	(0.117)	(0.0574)	(0.120)		
Observations	16,388	16,388	16,388	16,388	16,388	16,388	6,642	19,062	19,478	5,850	3,345	3,345

*Notes* : Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. Estimates in Panel A are based on a sample of all villages in border districts. In Panel A, DiD estimates are reported in columns 1 - 10 and OLS estimates are reported in columns 11 - 12. Estimates in Panel B are based on a sample of villages within 50 km from the border. In Panel B, DiDC estimates are reported in columns 1 - 10 and RD estimates are reported in columns 11 - 12. Columns 1 - 6 use measures related to firm activity, specifically the total number of firms (column 1), number of private firms (column 2), number of government firms (column 3), total non-farm employment (column 4), manufacturing employment (column 5), and industrial employment (column 6), as outcome variables. Columns 7 - 10 use measures of public goods provision, specifically the change in proportion of villages that have a middle school (column 7), healthcare center (column 8), telephone connection (column 9), and power for all purposes (column 10), as outcome variables. Columns 11 - 12 use measures of state's efficiency in implementing government programs, specifically the natural log of average productivity (average rate of new road construction) (column 11) and the natural log of average cost efficiency (ratio of stipulated to actual cost) (column 12) of new road construction projects between 2001 and 2015, as outcome variables. Specifications in columns 1 - 10 include pair-period FEs while specifications in columns 11 - 12 only include pair FEs.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 4: Mechanism Analysis - Proximity to State Capital (I)**

Specification:	Actual Split in 2000		Placebo Split in 1996	
	DiD	DiDC	DiD	DiDC
Sample:	All Villages in Border-Districts	Villages within 50km from Border	All Villages in Border-Districts	Villages within 50km from Border
	(1)	(2)	(3)	(4)
Dep. Var: Avg. Level of Lights Density				
Newstate	-0.509 (1.175)	8.035*** (1.971)	-0.435 (1.075)	7.000*** (1.870)
Dist. to State Cap.	-0.809** (0.340)	1.865*** (0.542)	-0.772** (0.307)	1.587*** (0.514)
Newstate × Dist. to State Cap.	-0.842*** (0.267)	-1.883*** (0.411)	-0.799*** (0.250)	-1.684*** (0.396)
Newstate × Post	3.845*** (0.449)	4.808*** (0.665)	-0.148 (0.393)	2.070*** (0.706)
Post × Dist. to State Cap.	0.109 (0.125)	0.306* (0.163)	-0.0747 (0.112)	0.556** (0.211)
Newstate × Post × Dist. to State Cap.	-1.124*** (0.124)	-1.510*** (0.136)	-0.0868 (0.0855)	-0.399*** (0.130)
Observations	40,940	24,942	40,940	24,942

*Notes*: Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. Estimates reported in columns 1 - 2 are based on the actual split in 2000 while estimates reported in columns 3 - 4 are based on the placebo split in 1996. For the actual split, the Pre-Split period spans 1993 - 2000 and the Post-Split period spans 2001 - 2013. For the placebo split, the Pre-Split period spans 1993 - 1996 and the Post-Split period spans 1997 - 2000. Specifications in all columns use the average level of nighttime lights density as the outcome variable. DiD estimates for a sample of all CH and MP villages in border districts are reported in columns 1 and 3 while DiDC estimates for a sample of villages within 50 km from the CH-MP border are reported in columns 2 and 4. Specifications in all columns include pair-period FEs.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 5: Mechanism Analysis - Proximity to State Capital (II)**

Outcome:	Firm-Level Activity and Non-Farm Employment						Delivery of Public Goods				Implementation	
	Firms (All)	Firms (Pvt)	Firms (Gov)	Non-Farm Emp.	Mfg. Emp.	Ind. Emp.	Schools	Health Cntr.	Telephone	Power	Productivity	Cost Efficiency
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Sample - All Villages in Border-Districts												
	DiD										OLS	
Newstate	-28.61* (15.44)	-25.92* (14.96)	-2.695*** (0.906)	-68.19** (31.97)	-37.66** (14.63)	-40.67** (15.68)	0.00341 (0.0354)	-0.293*** (0.0956)	-0.177* (0.0929)	0.312** (0.122)	0.865** (0.376)	-0.0761 (0.0792)
Dist. to State Cap.	-6.437 (4.142)	-5.878 (3.968)	-0.560* (0.305)	-16.46* (8.690)	-8.663** (3.497)	-9.629** (3.815)	0.000656 (0.0121)	-0.0755** (0.0351)	-0.0685** (0.0268)	0.107** (0.0358)	0.107 (0.101)	-0.0219 (0.0232)
Newstate × Dist. State Cap.	4.434 (3.846)	3.515 (3.677)	0.919*** (0.296)	10.82 (8.355)	6.101* (3.357)	6.616* (3.646)	-0.00831 (0.00794)	0.0180 (0.0204)	0.00463 (0.0209)	-0.0121 (0.0262)	-0.290*** (0.101)	0.0441** (0.0213)
Newstate × Post	22.36** (10.04)	23.17** (9.484)	-0.809 (1.290)	56.87** (26.22)	23.08*** (7.422)	21.79*** (7.572)	0.280*** (0.0968)	0.698*** (0.159)	0.171 (0.153)	-0.422 (0.317)		
Post × Dist. To State Cap.	0.143 (2.648)	0.987 (2.553)	-0.844** (0.365)	-1.059 (7.733)	2.937 (1.819)	2.516 (1.931)	0.0497 (0.0307)	0.190*** (0.0560)	0.0492 (0.0466)	-0.222** (0.0902)		
Newstate × Post × Dist. to State Cap.	-5.007** (2.283)	-4.760** (2.166)	-0.247 (0.317)	-11.12 (6.884)	-5.299*** (1.875)	-4.545** (1.946)	-0.0526*** (0.0198)	0.00820 (0.0381)	0.00654 (0.0310)	0.0600 (0.0850)		
Observations	27,290	27,290	27,290	27,290	27,290	27,290	11,320	31,684	32,274	10,392	4,875	4,875

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. Estimates in Panel A are based on a sample of all villages in border districts. In Panel A, DiD estimates are reported in columns 1 - 10 and OLS estimates are reported in columns 11 - 12. Estimates in Panel B are based on a sample of villages within 50 km from the border. In Panel B, DiDC estimates are reported in columns 1 - 10 and RD estimates are reported in columns 11 - 12. Columns 1 - 6 use measures related to firm activity, specifically the total number of firms (column 1), number of private firms (column 2), number of government firms (column 3), total non-farm employment (column 4), manufacturing employment (column 5), and industrial employment (column 6), as outcome variables. Columns 7 - 10 use measures of public goods provision, specifically the change in proportion of villages that have a middle school (column 7), healthcare center (column 8), telephone connection (column 9), and power for all purposes (column 10), as outcome variables. Columns 11 - 12 use measures of state's efficiency in implementing government programs, specifically the natural log of average productivity (average rate of new road construction) (column 11) and the natural log of average cost efficiency (ratio of stipulated to actual cost) (column 12) of new road construction projects between 2001 and 2015, as outcome variables. Specifications in columns 1 - 10 include pair-period FEs while specifications in columns 11 - 12 only include pair FEs.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 5 (Continued): Mechanism Analysis - Proximity to State Capital (II)**

Outcome:	Firm-Level Activity and Non-Farm Employment						Delivery of Public Goods				Implementation	
	Firms (All)	Firms (Pvt)	Firms (Gov)	Non-Farm Emp.	Mfg. Emp.	Ind. Emp.	Schools	Health Cntr.	Telephone	Power	Productivity	Cost Efficiency
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Sample - Villages within 50 km from Border												
	DiDC										RD	
Newstate	-13.13 (25.46)	-5.692 (23.01)	-7.441** (2.840)	-31.46 (56.88)	-8.763 (13.22)	-10.01 (16.37)	-0.0807* (0.0459)	-0.331* (0.183)	0.209 (0.138)	0.123 (0.144)	1.689*** (0.625)	-0.00119 (0.107)
Dist. to State Cap.	1.676 (6.680)	2.893 (6.018)	-1.217 (0.747)	2.959 (14.69)	-0.335 (3.424)	0.180 (4.273)	-0.0304** (0.0133)	-0.0832 (0.0511)	0.0537 (0.0403)	0.00920 (0.0315)	0.360** (0.145)	-0.0305 (0.0322)
Newstate × Dist. State Cap.	3.612 (5.730)	1.798 (5.163)	1.814*** (0.654)	10.49 (13.24)	1.651 (2.932)	2.397 (3.678)	0.0112 (0.0102)	-0.0171 (0.0371)	-0.0593* (0.0298)	0.0409 (0.0287)	-0.238 (0.154)	0.00222 (0.0220)
Newstate × Post	31.72 (27.87)	29.81 (27.77)	1.909 (2.222)	68.40 (81.46)	8.729 (8.620)	8.694 (9.978)	0.696*** (0.165)	1.091*** (0.336)	-0.403 (0.254)	-0.0908 (0.277)		
Post × Dist. To State Cap.	-6.263 (5.793)	-6.219 (5.818)	-0.0436 (0.652)	-19.92 (19.84)	0.494 (2.263)	-0.589 (2.650)	0.148*** (0.0458)	0.313*** (0.0936)	-0.132* (0.0768)	-0.0374 (0.0657)		
Newstate × Post × Dist. to State Cap.	-5.092 (5.571)	-4.153 (5.566)	-0.939** (0.403)	-9.028 (16.65)	-1.770 (1.812)	-2.180 (1.986)	-0.111*** (0.0320)	0.0122 (0.0692)	0.0886 (0.0551)	0.103 (0.0662)		
Observations	16,388	16,388	16,388	16,388	16,388	16,388	6,642	19,062	19,478	5,850	3,345	3,345

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. Estimates in Panel A are based on a sample of all villages in border districts. In Panel A, DiD estimates are reported in columns 1 - 10 and OLS estimates are reported in columns 11 - 12. Estimates in Panel B are based on a sample of villages within 50 km from the border. In Panel B, DiDC estimates are reported in columns 1 - 10 and RD estimates are reported in columns 11 - 12. Columns 1 - 6 use measures related to firm activity, specifically the total number of firms (column 1), number of private firms (column 2), number of government firms (column 3), total non-farm employment (column 4), manufacturing employment (column 5), and industrial employment (column 6), as outcome variables. Columns 7 - 10 use measures of public goods provision, specifically the change in proportion of villages that have a middle school (column 7), healthcare center (column 8), telephone connection (column 9), and power for all purposes (column 10), as outcome variables. Columns 11 - 12 use measures of state's efficiency in implementing government programs, specifically the natural log of average productivity (average rate of new road construction) (column 11) and the natural log of average cost efficiency (ratio of stipulated to actual cost) (column 12) of new road construction projects between 2001 and 2015, as outcome variables. Specifications in columns 1 - 10 include pair-period FEs while specifications in columns 11 - 12 only include pair FEs.

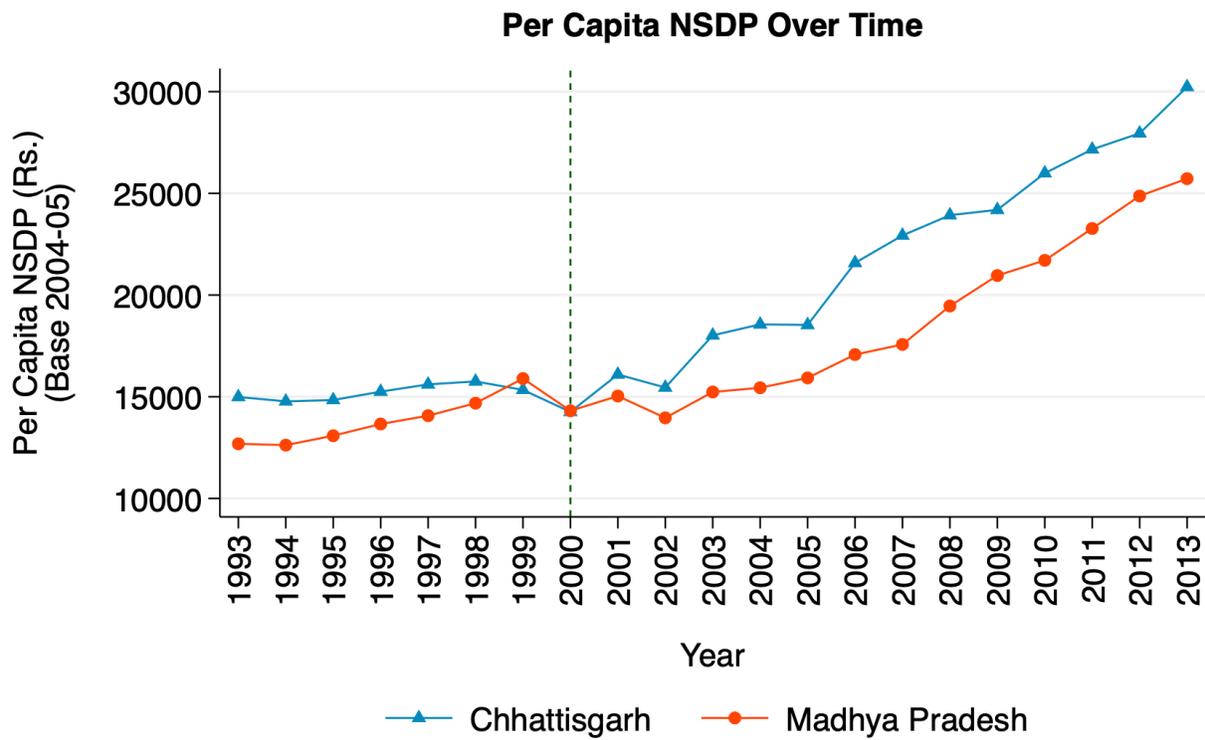
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 6: Mechanism Analysis - Political Accountability and Government Responsiveness**

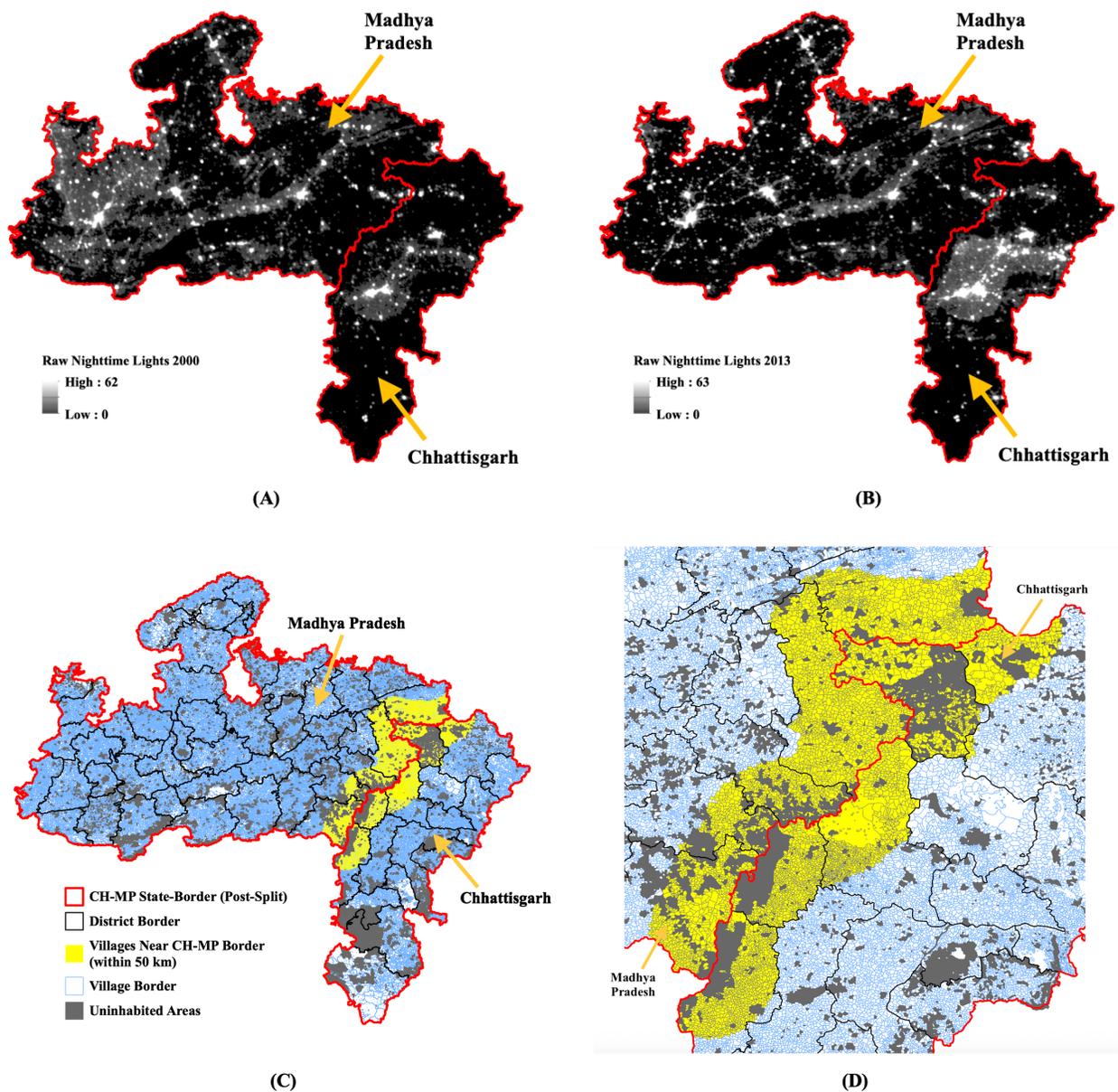
Dep. Var:	Sample: All CH-MP Constituencies		Sample: Constituencies in Border-Districts	
	Voter Turnout	Inv. Win Margin	Voter Turnout	Inv. Win Margin
	(1)	(2)	(3)	(4)
Newstate	-0.0225 (0.0226)	-0.0133 (0.00945)	0.0198 (0.0311)	-0.0280** (0.0112)
Newstate × Post	0.0538** (0.0214)	0.0334*** (0.0116)	0.00357 (0.0367)	0.0591*** (0.0119)
Observations	2,228	2,228	643	643
Pair-Period FEs	NO	NO	YES	YES

*Notes* : Standard errors (in parentheses) are clustered at the district level in columns 1 and 2 and at the district - pair level in columns 3 and 4. Diff-in-diff. estimates in columns 1 and 2 are based on a sample of elections held in all state-legislative assembly constituencies of CH and MP. Diff-in-diff. estimates in columns 3 and 4 are based on a sample of elections held in constituencies in border districts along CH-MP border. We use measures of political accountability and government responsiveness, specifically voter turnout ratio (columns 1 and 3) and inverse of the win margin (columns 2 and 4), as outcome variables.

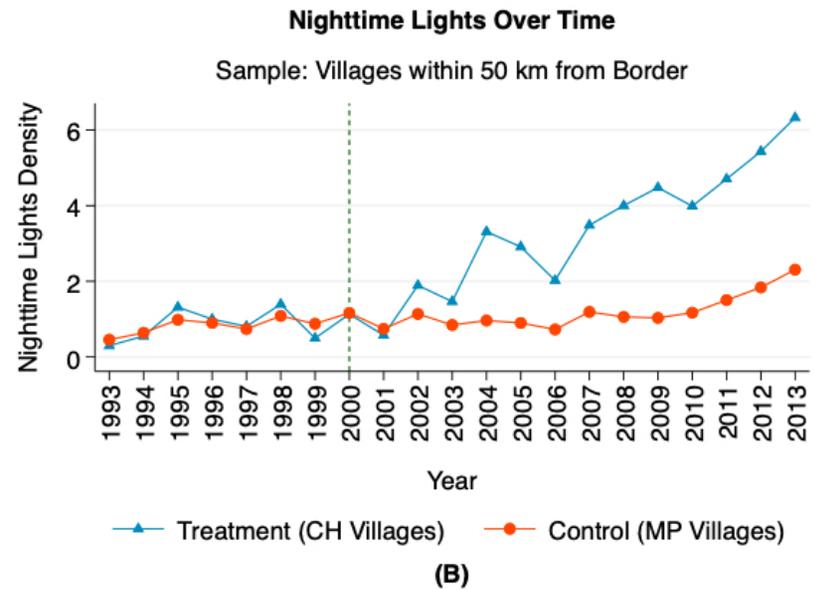
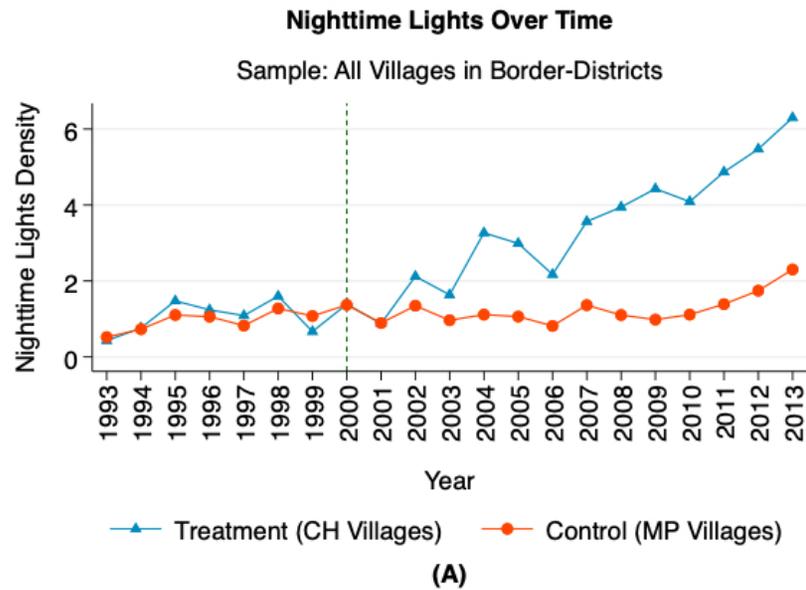
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1



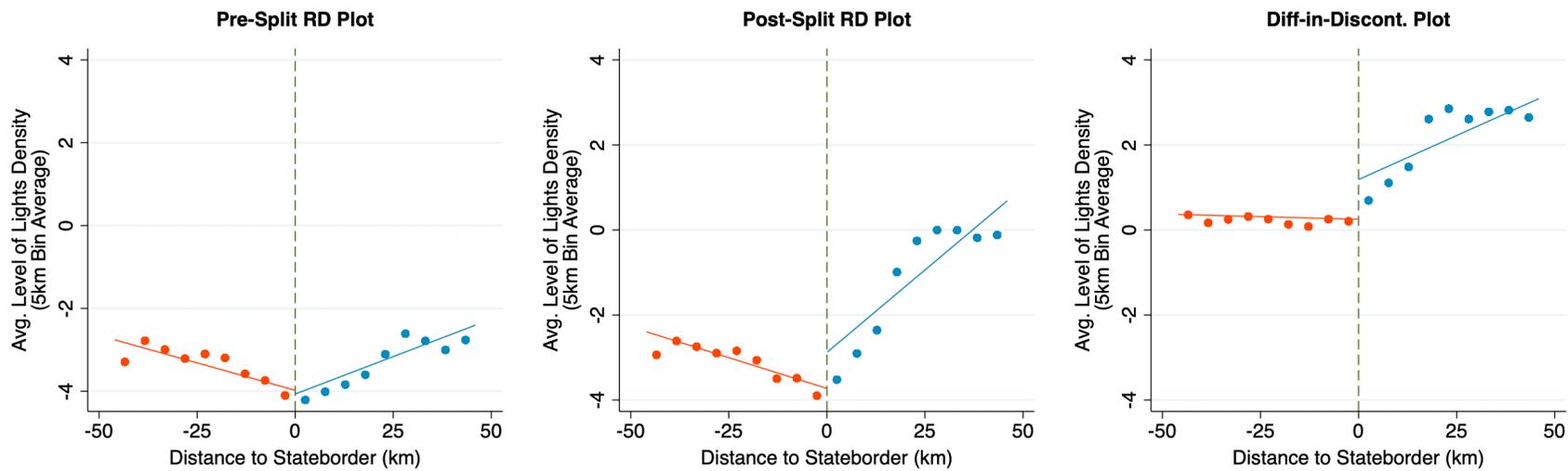
**Figure 1:** State-level Trends in Per Capita NSDP (Rs.) (Base 2004-05) of CH and MP Pre- and Post-Split.



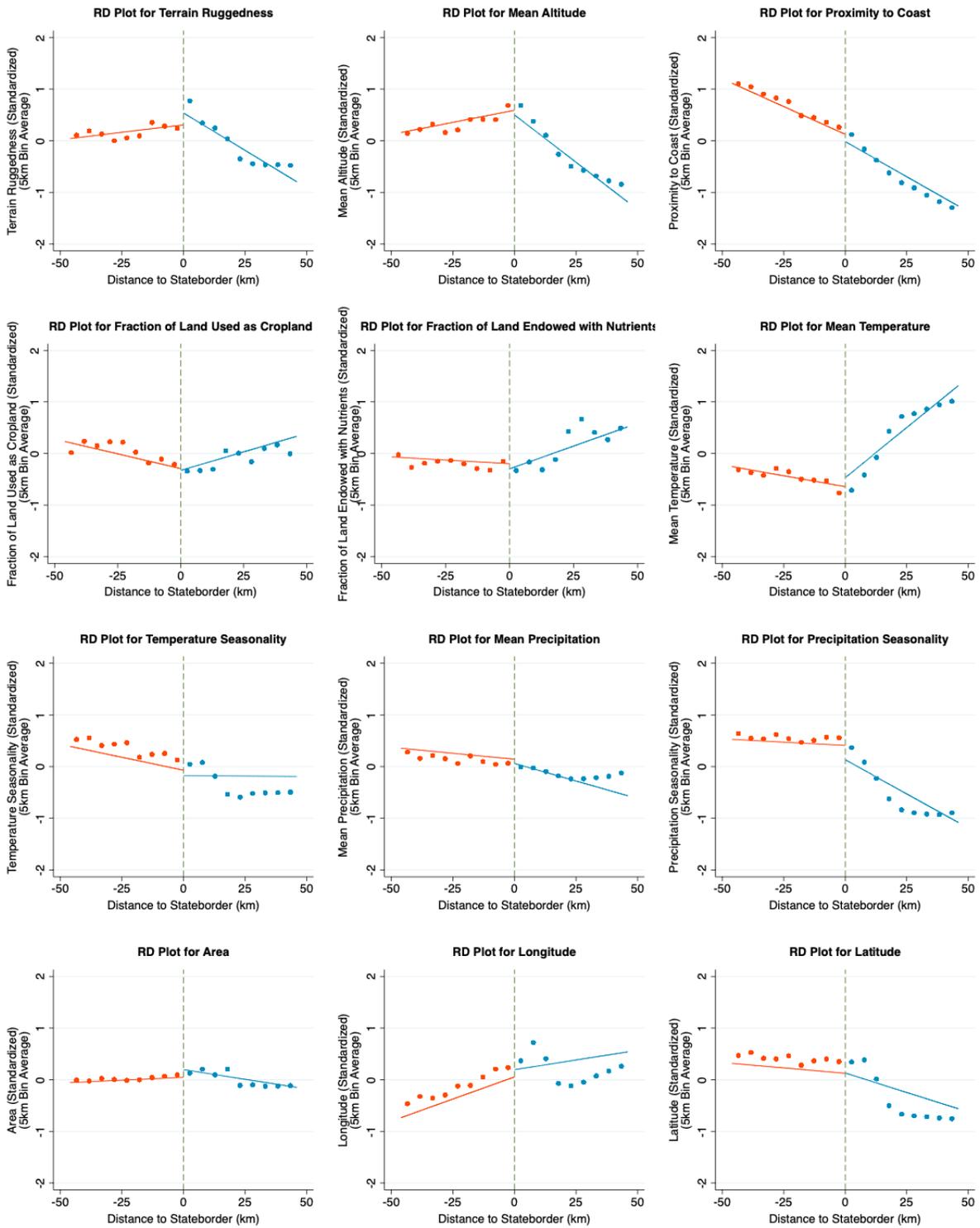
**Figure 2:** (A) Raw Nighttime Lights in CH and MP in 2000. (B) Raw Nighttime Lights in CH and MP in 2013. (C) Sample of Villages on Either Side of the CH-MP Border (Zoomed-Out View). (D) Sample of Villages on Either Side of the CH-MP Border (Zoomed-In View).



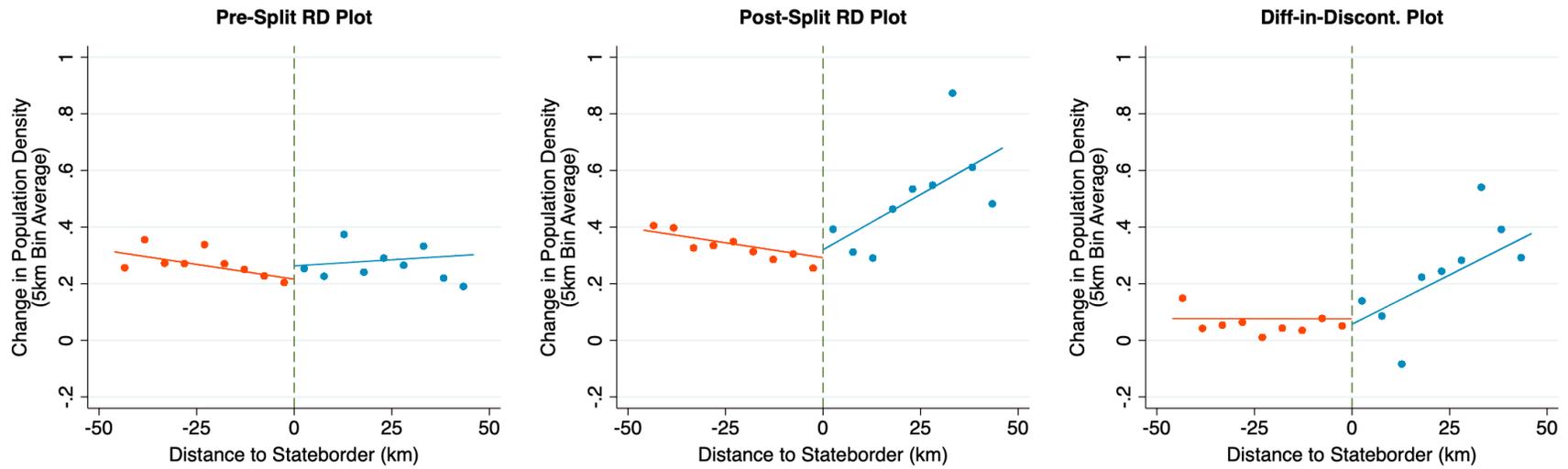
**Figure 3:** Trends in Nighttime Lights Density. **(A)** Trends in Nighttime Lights Density of CH and MP Villages in Border-Districts Pre- and Post-Split. **(B)** Trends in Nighttime Lights Density of CH and MP Villages within 50 km from Border Pre- and Post-Split.



**Figure 4:** Graphical Illustration of DiDC Results – Effect on Avg. Level of Nighttime Lights Density.



**Figure 5: Balance Tests of Time-Invariant Characteristics (Geography, Climate, Area, and Location).**



**Figure 6:** Validity Test for Manipulative Sorting of Population across the CH-MP border. **(A)** RD plot for Change in Population Density between 1991 and 2001 (Pre-Split). **(B)** RD plot for Change in Population Density between 2001 and 2011 (Post-Split). **(C)** Diff-in-Discont. Plot for Change in Population Density.

# **Regional Autonomy and Development: Evidence from Madhya Pradesh – Chhattisgarh Split in India\***

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## **Online Appendix**

JEL Codes: D72, H41, H70, H77, O10, O40

Keywords: state autonomy and control, responsive governance, economic development, proximity, capital, accountability

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## **Powers Granted to the State of Chhattisgarh Upon Creation**

Upon creation, the State of Chhattisgarh (CH) was accorded all powers that a ‘full’ State in India wields as guaranteed in India’s constitution. The Constitution of India grants exclusive legislative and administrative powers to the State governments over matters listed in the *State List* or *List-II* including the control over police forces, maintaining law and order, provision of public goods such as healthcare, sanitation, transportation, and electricity among others, land laws and policies, labor markets, money lending, state public services, and state retail taxes among others.

In concurrence with the Union (or central) government, the State governments also have powers in matters listed in the *Concurrent List* or *List-III* such as marriage and divorce, property transfer, education, civil procedure, economic and social planning, contracts, and newspapers among others. In addition to these, the State governments also have absolute autonomy in financial decisions such as authorizing expenditure of financial resources available to them for public purpose, taxation, as well as borrowing. The powers and rights granted to the State governments are so significant that they cannot be overruled by the union (or central) government.

After its creation from the State of Madhya Pradesh (MP), the CH state independently exercised powers over matters pertaining to areas within the *new* CH region.<sup>1</sup> These included the expenditure of funds, rights over respective land, articles, and goods, rights to collect property and land tax, and rights to recover loans and advances from respective local entities among others. The split marked that the CH state would be responsible for all assets and liabilities, within the CH region, undertaken previously by the parent MP state. Additional sources of credit and debt were to be divided between CH and MP according to the population ratio.

The CH state also reserved the right to constitute independent institutions after its creation. Upon creation, CH got a separate High Court that had full jurisdiction, powers, and authority over areas that became a part of CH and the High Court of MP ceased to have any jurisdiction over these areas.

Apart from judicial institutions, various other state agencies and undertakings were set up such as the Chhattisgarh State Warehousing Corporation (formed in May 2002), Chhattisgarh

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<sup>1</sup> Refer to Parts IV – X, specifically sections (items) 21 – 86, of the Madhya Pradesh Reorganization Act, 2000 for more information on transfer of power from parent MP to CH as well as rights of the *new* CH state government upon creation.

Board of Secondary Education (officially formed in September 2001), Chhattisgarh Housing Board (formed in February 2004), Chhattisgarh State Electricity Board (functional from December 2000), Chhattisgarh Text Book Corporation (formed in 2004), Chhattisgarh State Medicinal Plant Board (set up in 2004), and Chhattisgarh Human Rights Commission (functional from April 2001) among others.

For administrative purposes, two separate cadres of the Indian Administrative Service (IAS), Indian Police Service (IPS), and Indian Forest Service (IFS) were appointed, one for CH and one for MP. Furthermore, both states had independent rights to make adaptations and modifications to law, through repeal or necessary amendment, that was in effect prior to the split.

### **Different Forms of RD Polynomial**

Following Dell (2010), we use RD polynomials of varying orders in single as well as multi-dimensions. The single dimensional non-parametric (first-order) RD polynomial includes a linear polynomial in distance to State-border. This is defined as  $f(D_v) = \lambda_1 distance_v$ . The single dimensional semiparametric (high-order) RD polynomials include a quadratic polynomial in distance to State-border as well as an interacted quadratic polynomial in distance to State-border. The quadratic polynomial in distance to State-border is defined as  $f(D_v) = \lambda_1 distance_v + \lambda_2 distance_v^2$ . The interacted quadratic polynomial in distance to State-border is defined as  $f(D_v) = \lambda_1 distance_v + \lambda_2 distance_v \times Newstate_v + \lambda_2 distance_v^2 + \lambda_2 distance_v^2 \times Newstate_v$ . The multi-dimensional non-parametric RD polynomial includes a linear polynomial in latitude ( $y$ ) and longitude ( $x$ ). This is defined as  $f(x, y) = x + y$ . The multi-dimensional semiparametric polynomials include a quadratic and a cubic polynomial in latitude and longitude. The quadratic polynomial in latitude ( $y$ ) and longitude ( $x$ ) is defined as  $f(x, y) = x + y + x^2 + y^2 + xy$ . The cubic polynomial in latitude ( $y$ ) and longitude ( $x$ ) is defined as  $f(x, y) = x + y + x^2 + y^2 + xy + x^3 + y^3 + x^2y + xy^2$ . Note that the higher-order polynomials are generally used for larger bandwidths.

## OLS Estimation

Estimation of columns 11 – 12 in Panel A of Table 3:

The OLS estimates in columns 11 – 12 of Panel A of Table 3 are based on a sample of all villages within border-districts. Specification used to obtain the respective OLS estimates is as follows

$$y_{v,p} = \alpha_1 + \beta_1 Newstate_v + \gamma_p + \varepsilon_{v,p}$$

where  $\beta_1$  represents the OLS estimate and  $\gamma_p$  represents border-pair fixed effects which allow comparison of villages within border-district pairs  $p$ . Standard errors are clustered at the subdistrict ( $i$ ) – district ( $d$ ) – pair ( $p$ ) level in these OLS estimations.

## RD Estimation

Estimation of columns 11 – 12 in Panel B of Table 3 as well as all columns in Table A2:

The RD estimates in columns 11 – 12 of Panel B of Table 3 and all columns in Table A2 are based on a sample of villages within 50 km from the CH-MP border on either side. Specification used to obtain the respective RD estimates is as follows

$$y_{v,p} = \alpha_1 + \beta_1 Newstate_v + f(D_v) + \gamma_p + \varepsilon_{v,p}$$

where  $\beta_1$  represents the RD estimate,  $\gamma_p$  represents border-pair fixed effects which allow comparison of villages within border-district pairs  $p$ , and  $f(D_v)$  represents the RD polynomial used in estimation. We use a first-order interacted linear polynomial in distance to state-border, described in the equation below, as the RD polynomial  $f(D_v)$ . Standard errors are clustered at the subdistrict ( $i$ ) – district ( $d$ ) – pair ( $p$ ) level in these RD estimations.

$$f(D_v) = \lambda_1 distance_v + \lambda_2 distance_v \times Newstate_v$$

## Data Appendix

### Shapefiles:

- 1.) *Village-level Shapefiles:* We refer to the India Village-Level Geospatial Socio-Economic Data Set, v1 (1991, 2001) for the 2001 village-level shapefiles of India. This dataset is compiled by the NASA Socioeconomic Data and Applications Center (SEDAC) which is hosted by the Center for International Earth Science Information Network (CIESIN) of the Columbia Climate School at Columbia University. This dataset digitizes village/town level boundaries from the official analog maps published by the Survey of India for 2001 and is distributed as separate shapefiles for each of the 28 States (as per Census 2001) and combined Union Territories for 2001.<sup>2</sup> We merge the individual shapefiles of CH and MP in ArcGIS to obtain a single 2001 village-level shapefile for CH and MP. We also construct a 2001 village-level shapefile for the whole of India by merging all the individual shapefiles in ArcGIS.<sup>3</sup>
- 2.) *State-level Shapefile:* We obtain the 2001 State-level shapefile from DataMeet which is an open data platform that houses a wide variety of data repositories for India.<sup>4</sup> Contributors of DataMeet have compiled state and district-level shapefiles for India as per the 2001 and 2011 Census boundaries.

### SHRUG keys:

For non-GIS data at the village-level, we use a set of *keys*, developed by the Socioeconomic High-resolution Rural-Urban Geographic (SHRUG) open data platform, in matching data to the 2001 Census village-boundaries. The SHRUG platform developed these *keys* by matching towns and villages across population and economic censuses from 1990 to 2013 taking into account splits, merges, and other boundary changes. These *keys* consist of a unique SHRUG identifier, known as *shrid*, which represents a geographical unit that can be consistently mapped across all census rounds from 1990 – 2013. While a *shrid* represents a single village or town in majority cases, there

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<sup>2</sup> See Meiyappan et al. (2016) and Meiyappan et al. (2018) for more information on the India Village-Level Geospatial Socio-Economic Data Set, v1 (1991, 2001).

<sup>3</sup> The India Village-Level Geospatial Socio-Economic Data Set, v1 (2001) does not contain village-level data for 3 North-Eastern States (Arunachal Pradesh, Nagaland, Meghalaya) and the 7 Union Territories (Chandigarh, Delhi, Daman and Diu, Dadra and Nagar Haveli, Lakshadweep, Puducherry, and Andaman and Nicobar Islands). In such cases, the geospatial data set provides sub-district/taluka/tehsil level data instead. We exclude these 3 States and 7 Union Territories in our construction of the 2001 village-level shapefile for the whole of India.

<sup>4</sup> The various data repositories compiled by DataMeet can be found at <https://github.com/datameet>.

are some cases where a *shrid* represents a district and sometimes even an entire city/state. We drop these odd *shrids* as well as *shrids* that represent a town from our village-level sample in this paper. See Asher et al. (2021) for additional information on the SHRUG open data platform.

#### Nighttime Lights Data:

We obtain nighttime lights data for our analysis from Li et al. (2020). This data is in the form of images of nighttime luminosity generated from the earth's surface. Each image is made up of billions of pixels (approx.  $1\text{ km} \times 1\text{ km}$  grids), each emitting varying intensities of nighttime luminosity measured using a digital number (DN) that ranges from 0 – 63. Using tools in ArcGIS, we superimpose the nighttime luminosity image for a particular year with the respective region's shapefile and obtain the following data: 1.) Count (total #) of pixels in that region. 2.) Sum of Nighttime Lights which is equivalent to the summation of DNs of all pixels in that region. 3.) Average Nighttime Lights (Average DN) emitted from a pixel in that region. While tools in ArcGIS directly generate the Average Nighttime Lights measure, the Average Nighttime Lights emitted from a pixel in that region can also be computed by dividing the sum of DNs of all pixels in that region by the count (total #) of pixels in that region. Since pixels are approx.  $1\text{ km}^2$  grids, the Average Nighttime Lights measure is equivalent to Nighttime Lights per sq. km. or the Nighttime Lights Density of that region for that year.

#### Geography, Climate, Area, and Location:

- 1.) *Terrain Ruggedness (100m)*: GIS data on terrain ruggedness is obtained from Nunn and Puga (2012). We extract the Terrain Ruggedness (100m) index for villages in our sample in ArcGIS.<sup>5</sup>
- 2.) *Mean Altitude (m)*: Raw data on elevation at 30 arc-seconds (approximately  $1\text{ km}^2$  at the equator) is obtained from DIVA-GIS.<sup>6</sup> The original data source for the elevation data is the SRTM30 (Shuttle Radar Topography Mission) dataset provided by the CGIAR-CSI GeoPortal. Using this data and tools in ArcGIS, we obtain the mean elevation (m) for villages in our sample.

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<sup>5</sup> See Jha and Talathi (2024) and Chanda and Kabiraj (2020) for additional information on the Terrain Ruggedness data. The GIS file for this data can be found at <https://diegopuga.org/data/rugged/#grid>.

<sup>6</sup> DIVA-GIS provides free spatial data for the whole world. Data include inland water (rivers, canals, lakes), elevation, administrative boundaries, roads, railroads, and land cover.

- 3.) *Proximity to the nearest coastline (km)*: We import the coastal boundary shapefile of India, obtained from Natural Earth Data<sup>7</sup>, into ArcGIS and compute the distance to the nearest coastline (km) from the centroid of each village in our sample.
- 4.) *Fraction of land used as cropland and Fraction of land endowed with nutrients*: Data on land cover characteristics is obtained from the Global Land Cover Characteristics Data Base Version 2.0 and is available at a resolution of 30 arc-seconds (approximately 1 km<sup>2</sup> at the equator). While there are seven derived data sets in the global land cover data base, we follow Pinkovskiy (2017) and use the International Geosphere Biosphere Programme (IGBP) Land Cover Classification (Loveland and Belward, 1997). In ArcGIS, we compute the fraction of land used as cropland (value 12 in the IGBP land cover legend) as well as the fraction of land endowed with nutrients (value 14 in the IGBP land cover legend) for each village in our sample.
- 5.) *Mean Temperature (°C), Temperature Seasonality (standard deviation ×100), Mean Precipitation (mm), and Precipitation Seasonality (Coefficient of Variation)*: Climate data is obtained from WorldClim version 2.1.<sup>8</sup> We get data on four bioclimatic variables, namely mean temperature (°C) (BIO1), temperature seasonality (standard deviation x100) (BIO4), mean precipitation (mm) (BIO12), and precipitation seasonality (coefficient of variation) (BIO14), that have been averaged from monthly data for years 1970 – 2000. We extract these four bioclimatic variables for each village in our sample in ArcGIS.
- 6.) *Area (sq. km)*: We compute the area (sq. km) of each village in our sample using tools in ArcGIS.
- 7.) *Longitude and Latitude*: We extract the longitude and latitude of the centroid of each village in our sample using tools in ArcGIS.

#### Population Density Data from Village-level Census:

We obtain village-level data on population density for years 1991, 2001, and 2011 from the SHRUG open data platform (Asher et al., 2021). The data is originally sourced from the primary

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<sup>7</sup> Vector and raster map data at 1:10m, 1:50m, and 1:110m scaled is made available publicly on Natural Earth Data. This data is distributed across three categories: cultural, physical, and raster. The coastal boundary shapefile for India can be found under the physical category at the 1:10m scale. Additional information on Natural Earth Data can be found in Jha and Talathi (2024), Chanda and Kabiraj (2020), and <https://www.naturalearthdata.com/>.

<sup>8</sup> See Fick and Hijmans (2017) and Pinkovskiy (2017) for more information on data available at WorldClim.

census abstract published as a part of 1991, 2001, and 2011 Census. We match this data to the villages in our sample using SHRUG *keys* described previously.

#### Firm Activity Data from Economic Census:

We obtain data on the number of non-agricultural firms and non-farm employment from the SHRUG open data platform that has compiled data from the Economic Census of 1990 (3<sup>rd</sup> round), 1998 (4<sup>th</sup> round), 2005 (5<sup>th</sup> round), and 2013 (6<sup>th</sup> round).<sup>9</sup> We match this data to the villages in our sample using SHRUG *keys* described previously. In light of the changes that have occurred over time in the National Industrial Classification (NIC) codes across the various rounds of the Economic Census, the SHRUG team has constructed a set of *SHRIC* (SHRUG Industrial Classification) codes which is essentially a harmonized version of industrial classification codes across the various of NIC codes. We map the SHRIC codes to the 3-digit NIC 2008 and construct sectoral non-farm employment variables, specifically manufacturing and industrial employment.<sup>10</sup> We focus on firm activity data from the Economic Census of 1998 and 2013 in our analysis.<sup>11</sup>

#### Public Goods (Amenities) Data from Village-level Census:

We obtain village-level data on public goods (amenities), specifically the availability of a middle school, healthcare center<sup>12</sup>, telephone connection, and power for all uses, for years 1991, 2001, and 2011 from the SHRUG open data platform (Asher et al., 2021). These are dummy variables that take a value of 1 if a village has the respective public good and 0 otherwise. The data is originally sourced from the village-level directories (VD) published as a part of 1991, 2001, and 2011 Census. We match this data to the villages in our sample using SHRUG *keys* described previously. We construct measures of public goods provision, specifically the change in the proportion of villages that have a middle school, healthcare center, telephone connection, and power for all purposes. The change between 1991 and 2001 captures the period before the split,

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<sup>9</sup> The Economic Census is conducted by the Central Statistics Organization, Ministry of Statistics and Programme Implementation, Government of India. The raw data can be accessed at <https://microdata.gov.in/nada43/index.php/catalog/ECO>.

<sup>10</sup> Industrial employment is the summation of employment in manufacturing (registered and unregistered), construction, electricity, gas, and water supply, and mining and quarrying sectors.

<sup>11</sup> Economic Census data for 1990 and 2005 is largely missing for a majority of CH villages in our sample. Out of the observations available for CH villages near the border for years 1998 and 2013, the 1990 and 2005 data is only available for 27% of these observations.

<sup>12</sup> In our analysis, a village is defined to have a healthcare center if it had either of the following: a maternity and child welfare center, a primary health center, primary health sub-center, or a dispensary.

when CH was part of MP, while the change between 2001 and 2011 captures the period after the split.

#### State's Implementation Efficiency from Village-level PMGSY Administrative Data:

We use administrative data of the PMGSY at the village-level in constructing measures of the state's efficiency in implementing government programs.<sup>13</sup> This data has been compiled by Asher and Novosad (2020) and is available on the SHRUG open data platform (Asher et al., 2021). The data is originally sourced from the PMGSY website (<https://omms.nic.in>). The dataset contains administrative information related to each road construction project in respective villages including the length (km) of road constructed under each project, time (days) taken to complete each project, and the actual and stipulated cost of each project among others. We construct two measures, specifically the average productivity (average rate of road construction) and the average cost efficiency (ratio of stipulated to actual cost) of road construction projects in a village between 2001 and 2015.<sup>14</sup> We match this data to the villages in our sample using SHRUG *keys* described previously.

#### Voter Turnout and Win Margin Data for State-legislative Elections:

We obtain data on voter turnout ratio and win margin at the constituency-level for state-legislative assembly elections held before (1985, 1990, 1993, 1998) and after the bifurcation (2003, 2008, 2013) in CH and MP from the SHRUG open data platform (Asher et al., 2021). This data is originally sourced from the Trivedi Center for Political Data (Jensenius and Verniers, 2017). The dataset includes information on voter turnout and vote share, among others, at the candidate-level as well as the election-level for each constituency. We measure the degree of participation and competitiveness in state-legislative elections in each constituency by voter turnout and inverse of the win margin<sup>15</sup> respectively.<sup>16</sup> SHRUG team provides identifiers to allow matching of constituency level data to districts. However, these are only available for elections starting in 2008

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<sup>13</sup> See Asher and Novosad (2020) and Lehne et al. (2018) for more information on the PMGSY as well as the use of PMGSY administrative data.

<sup>14</sup> Following Asher and Novosad (2020), we primarily focus on villages that did not have a paved road in (or by) 2001 and where *new* road construction projects (under the PMGSY) were undertaken and implemented by the respective State administration between 2001 and 2015.

<sup>15</sup> Inverse of the win margin =  $1 - \text{Win Margin}$ , where win margin is the difference in vote shares of the winner and runner-up in State-legislative elections.

<sup>16</sup> See Besley and Burgess (2002), Jha and Talathi (2024), Ardanaz et al. (2014)

i.e., after the delimitation. We match constituency level data, for elections starting in 2008, to the districts in our sample using these identifiers. For the remaining constituency level data i.e., elections before 2008, we manually match constituency level data to districts in our sample.<sup>17</sup>

### Proximity to the State Capital and the State-Border

After the creation of CH, Raipur became the capital of the *new* CH state while Bhopal continued to be the capital of MP. We compute the geodesic distance from the centroid of each village in CH and MP to Raipur and Bhopal respectively as well as the CH-MP state-border border in ArcGIS using the 2001 state and village-level shapefiles of India.

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<sup>17</sup> We refer to websites, such as <https://www.myneta.info/> among others, for this.

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**Table A1: Summary Statistics of Nighttime Lights Measures across all Villages in India**

Variables	Obs	Mean	Std. Dev.	Min.	Max.
<i>Panel A: Summary Statistics for Sum of Nighttime Lights</i>					
Inter-Calibrated DMSP Data 2009	509,588	35.020	180.902	0	63219
Inter-Calibrated DMSP Data 2010	509,588	34.433	179.942	0	62487
Inter-Calibrated DMSP Data 2011	509,588	36.535	187.054	0	61468
Inter-Calibrated DMSP Data 2012	509,588	40.382	196.100	0	64736
Inter-Calibrated DMSP Data 2013	509,588	39.795	196.381	0	65248
DMSP-like VIIRS Data 2013	509,588	60.661	400.439	0	244642
<i>Panel B: Summary Statistics for Nighttime Lights Density</i>					
Inter-Calibrated DMSP Data 2009	509,588	4.973	7.320	0	59
Inter-Calibrated DMSP Data 2010	509,588	4.945	7.107	0	59
Inter-Calibrated DMSP Data 2011	509,588	5.243	7.408	0	63
Inter-Calibrated DMSP Data 2012	509,588	5.821	8.152	0	63
Inter-Calibrated DMSP Data 2013	509,588	5.821	8.124	0	63
DMSP-like VIIRS Data 2013	509,588	9.089	6.910	0	63

*Notes:* Panel A reports summary statistics for *Sum of Nighttime Lights* obtained using Inter-Calibrated DMSP data (for years 2009 – 2013) as well as DMSP-like data from VIIRS (for year 2013) for all villages in India. Panel B reports summary statistics for *Nighttime Lights Density* obtained using Inter-Calibrated DMSP data (for years 2009 – 2013) as well as DMSP-like data from VIIRS (for year 2013) for all villages in India.

**Table A2: Balance Tests of Time-Invariant Characteristics**

Dependent Variable:	Geography					Climate				Area	Location	
	Terrain Rugg. (1)	Mean Altitude (2)	Proximity to Coast (3)	Frac. Cropland (4)	Frac. Nutrients (5)	Mean Temp. (6)	Temp. Seasonality (7)	Mean Precip. (8)	Precip. Seasonality (9)	Area (10)	Longitude (11)	Latitude (12)
Newstate	0.221 (0.182)	-0.144 (0.217)	-0.0910 (0.130)	-0.0362 (0.162)	-0.0749 (0.167)	0.221 (0.209)	-0.0735 (0.149)	-0.153 (0.173)	-0.370 (0.258)	0.179** (0.0852)	0.100 (0.113)	0.0148 (0.103)
Observations	12,471	12,471	12,471	12,469	12,469	12,471	12,471	12,471	12,471	12,471	12,471	12,471

*Notes*: Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. Each column reports the regression discontinuity (RD) estimate obtained using the respective time-invariant characteristic as the outcome variable. Outcome variables measuring geography include terrain ruggedness (100 m) (column 1), mean altitude (m) (column 2), proximity to the nearest coastline (km) (column 3), fraction of land used as cropland (column 4), and fraction of land endowed with nutrients (column 5). Outcome variables measuring climate include mean temperature (°C) (column 6), temperature seasonality (standard deviation  $\times 100$ ) (column 7), mean precipitation (mm) (column 8), and precipitation seasonality (coefficient of variation) (column 9). Area (sq. km) is used as the outcome variable in column 10. Outcome variables measuring location include longitude (decimal degrees) (column 11) and latitude (decimal degrees) (column 12). Outcome variables in all columns are standardized to have a mean of 0 and a standard deviation of 1. *Newstate* represents the treatment variable that takes a value of 1 if a village eventually became a part of the new state of Chhattisgarh and 0 otherwise. A first-order interacted linear polynomial in distance to state-border is used as the RD polynomial in all estimations.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A3: Robustness to Spatial Correlation (Sample: All Villages in Border-Districts)**

	Baseline	Conley Standard Errors (Conley, 1999)				Clustering at Spatially Higher Levels (Burgess et al., 2016)	
		Spatial Correlation Distance Cutoff				Grid-level	Grid - District - Pair level
		25 km	50 km	75 km	100 km		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	
<b>Panel A: Effect on Nighttime Lights Density (DiD Estimates)</b>							
Outcome: Avg. Level of Lights Density							
Newstate × Post	1.824*** (0.163)	1.824*** [0.163]	1.824*** [0.242]	1.824*** [0.288]	1.824*** [0.326]	1.824*** (0.0912)	1.824*** (0.0600)
Observations	40,940	40,940	40,940	40,940	40,940	40,940	40,940
<b>Panel B: Effect on Firm-Level Activity and Non-Farm Employment (DiD Estimates)</b>							
Outcome: Firms (All)							
Newstate × Post	13.66*** (2.865)	13.66*** [3.717]	13.66*** [4.066]	13.66*** [3.811]	13.66*** [3.690]	13.66*** (3.019)	13.66*** (1.934)
Observations	27,290	27,290	27,290	27,290	27,290	27,290	27,290
Outcome: Firms (Pvt)							
Newstate × Post	12.94*** (2.723)	12.94*** [3.706]	12.94*** [3.984]	12.94*** [3.632]	12.94*** [3.461]	12.94*** (2.992)	12.94*** (1.908)
Observations	27,290	27,290	27,290	27,290	27,290	27,290	27,290
Outcome: Firms (Gov)							
Newstate × Post	0.715** (0.307)	0.715*** [0.265]	0.715** [0.332]	0.715* [0.368]	0.715* [0.389]	0.715*** (0.204)	0.715*** (0.151)
Observations	27,290	27,290	27,290	27,290	27,290	27,290	27,290
Outcome: Non-Farm Emp.							
Newstate × Post	40.69*** (8.156)	40.69*** [10.37]	40.69*** [10.35]	40.69*** [9.462]	40.69*** [8.958]	40.69*** (9.631)	40.69*** (6.534)
Observations	27,290	27,290	27,290	27,290	27,290	27,290	27,290
Outcome: Mfg. Emp.							
Newstate × Post	7.480*** (1.766)	7.480*** [1.917]	7.480*** [2.161]	7.480*** [2.132]	7.480*** [1.986]	7.480*** (1.453)	7.480*** (1.041)
Observations	27,290	27,290	27,290	27,290	27,290	27,290	27,290
Outcome: Ind. Emp.							
Newstate × Post	8.412*** (1.805)	8.412*** [2.001]	8.412*** [2.195]	8.412*** [2.128]	8.412*** [1.939]	8.412*** (1.602)	8.412*** (1.162)
Observations	27,290	27,290	27,290	27,290	27,290	27,290	27,290

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level in the baseline specification in column 1. Conley Standard Errors (in square brackets) for varying spatial correlation distance cutoffs are reported in columns 2 - 5. Standard errors (in parentheses) are clustered at the grid-level (approx. 10 km × 10 km) in column 6 and at the grid - district - pair level in column 7. DiD estimates are reported in all columns of Panels A - C. DiD specifications in Panels A - C include pair-period FEs. OLS estimates are reported in all columns of Panel D. OLS specifications in Panel D include pair FEs. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A3 (Continued): Robustness to Spatial Correlation (Sample: All Villages in Border-Districts)**

	Baseline	Conley Standard Errors (Conley, 1999)				Clustering at Spatially Higher Levels (Burgess et al., 2016)	
		Spatial Correlation Distance Cutoff				Grid-level	Grid - District - Pair level
		25 km	50 km	75 km	100 km		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	
<b>Panel C: Effect on Delivery of Public Goods (DiD Estimates)</b>							
Outcome: Schools							
Newstate × Post	0.0729*** (0.0188)	0.0729*** [0.0200]	0.0729*** [0.0219]	0.0729*** [0.0226]	0.0729*** [0.0227]	0.0729*** (0.0181)	0.0729*** (0.0133)
Observations	11,320	11,320	11,320	11,320	11,320	11,320	11,320
Outcome: Health Cntr.							
Newstate × Post	0.279*** (0.0477)	0.279*** [0.0318]	0.279*** [0.0386]	0.279*** [0.0442]	0.279*** [0.0473]	0.279*** (0.0212)	0.279*** (0.0182)
Observations	31,684	31,684	31,684	31,684	31,684	31,684	31,684
Outcome: Telephone							
Newstate × Post	0.0693** (0.0282)	0.0693** [0.0320]	0.0693** [0.0337]	0.0693** [0.0343]	0.0693** [0.0333]	0.0693*** (0.0265)	0.0693*** (0.0193)
Observations	32,274	32,274	32,274	32,274	32,274	32,274	32,274
Outcome: Power							
Newstate × Post	0.190** (0.0766)	0.190*** [0.0605]	0.190** [0.0746]	0.190** [0.0809]	0.190** [0.0853]	0.190*** (0.0434)	0.190*** (0.0344)
Observations	10,392	10,392	10,392	10,392	10,392	10,392	10,392
<b>Panel D: Effect on Implementation Efficiency (OLS Estimates)</b>							
Outcome: Productivity							
Newstate × Post	0.144** (0.0646)	0.144** [0.0597]	0.144** [0.0683]	0.144* [0.0766]	0.144* [0.0818]	0.144*** (0.0449)	0.144*** (0.0325)
Observations	4,875	4,875	4,875	4,875	4,875	4,875	4,875
Outcome: Cost Efficiency							
Newstate × Post	0.0470*** (0.0148)	0.0470*** [0.0169]	0.0470** [0.0204]	0.0470** [0.0208]	0.0470** [0.0198]	0.0470*** (0.0131)	0.0470*** (0.00931)
Observations	4,875	4,875	4,875	4,875	4,875	4,875	4,875

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level in the baseline specification in column 1. Conley Standard Errors (in square brackets) for varying spatial correlation distance cutoffs are reported in columns 2 - 5. Standard errors (in parentheses) are clustered at the grid-level (approx. 10 km × 10 km) in column 6 and at the grid - district - pair level in column 7. DiD estimates are reported in all columns of Panels A - C. DiD specifications in Panels A - C include pair-period FEs. OLS estimates are reported in all columns of Panel D. OLS specifications in Panel D include pair FEs. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A4: Robustness to Spatial Correlation (Sample: Villages within 50 km from Border)**

	Baseline	Conley Standard Errors (Conley, 1999)				Clustering at Spatially Higher Levels (Burgess et al., 2016)	
		Spatial Correlation Distance Cutoff				Grid-level	Grid - District - Pair level
		25 km	50 km	75 km	100 km		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	
<b>Panel A: Effect on Nighttime Lights Density (DiDC Estimates)</b>							
Outcome: Avg. Level of Lights Density							
Newstate × Post	1.071*** (0.292)	1.071*** [0.290]	1.071*** [0.313]	1.071*** [0.357]	1.071*** [0.384]	1.071*** (0.195)	1.071*** (0.133)
Observations	24,942	24,942	24,942	24,942	24,942	24,942	24,942
<b>Panel B: Effect on Firm-Level Activity and Non-Farm Employment (DiDC Estimates)</b>							
Outcome: Firms (All)							
Newstate × Post	36.71** (14.12)	36.71*** [11.83]	36.71** [15.89]	36.71** [18.12]	36.71* [19.53]	36.71*** (9.468)	36.71*** (5.999)
Observations	16,388	16,388	16,388	16,388	16,388	16,388	16,388
Outcome: Firms (Pvt)							
Newstate × Post	36.56** (13.77)	36.56*** [11.57]	36.56** [15.45]	36.56** [17.60]	36.56* [18.95]	36.56*** (9.311)	36.56*** (5.883)
Observations	16,388	16,388	16,388	16,388	16,388	16,388	16,388
Outcome: Firms (Gov)							
Newstate × Post	0.147 (0.661)	0.147 [0.567]	0.147 [0.749]	0.147 [0.837]	0.147 [0.823]	0.147 (0.415)	0.147 (0.313)
Observations	16,388	16,388	16,388	16,388	16,388	16,388	16,388
Outcome: Non-Farm Emp.							
Newstate × Post	98.52*** (36.69)	98.52*** [31.58]	98.52** [39.21]	98.52** [43.26]	98.52** [44.82]	98.52*** (27.41)	98.52*** (18.46)
Observations	16,388	16,388	16,388	16,388	16,388	16,388	16,388
Outcome: Mfg. Emp.							
Newstate × Post	4.016** (2.004)	4.016 [2.889]	4.016 [3.114]	4.016 [2.934]	4.016 [2.904]	4.016* (2.425)	4.016** (1.601)
Observations	16,388	16,388	16,388	16,388	16,388	16,388	16,388
Outcome: Ind. Emp.							
Newstate × Post	5.781** (2.480)	5.781* [3.275]	5.781 [3.566]	5.781* [3.387]	5.781* [3.178]	5.781** (2.772)	5.781*** (1.914)
Observations	16,388	16,388	16,388	16,388	16,388	16,388	16,388

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level in the baseline specification in column 1. Conley Standard Errors (in square brackets) for varying spatial correlation distance cutoffs are reported in columns 2 - 5. Standard errors (in parentheses) are clustered at the grid-level (approx. 10 km × 10 km) in column 6 and at the grid - district - pair level in column 7. DiDC estimates are reported in all columns of Panels A - C. DiDC specifications in Panels A - C include pair-period FEs. RD estimates are reported in all columns of Panel D. RD specifications in Panel D include pair FEs. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A4 (Continued): Robustness to Spatial Correlation (Sample: Villages within 50 km from Border)**

	Baseline	Conley Standard Errors (Conley, 1999)				Clustering at Spatially Higher Levels (Burgess et al., 2016)	
		Spatial Correlation Distance Cutoff				Grid-level	Grid - District - Pair level
		25 km	50 km	75 km	100 km		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	
<b>Panel C: Effect on Delivery of Public Goods (DiDC Estimates)</b>							
Outcome: Schools							
Newstate × Post	0.117*** (0.0427)	0.117** [0.0532]	0.117** [0.0547]	0.117** [0.0536]	0.117** [0.0532]	0.117** (0.0515)	0.117*** (0.0352)
Observations	6,642	6,642	6,642	6,642	6,642	6,642	6,642
Outcome: Health Cntr.							
Newstate × Post	0.378*** (0.117)	0.378*** [0.0824]	0.378*** [0.0847]	0.378*** [0.0982]	0.378*** [0.0984]	0.378*** (0.0640)	0.378*** (0.0519)
Observations	19,062	19,062	19,062	19,062	19,062	19,062	19,062
Outcome: Telephone							
Newstate × Post	0.0953 (0.0574)	0.0953 [0.0727]	0.0953 [0.0645]	0.0953 [0.0633]	0.0953 [0.0596]	0.0953 (0.0605)	0.0953** (0.0429)
Observations	19,478	19,478	19,478	19,478	19,478	19,478	19,478
Outcome: Power							
Newstate × Post	0.187 (0.120)	0.187 [0.190]	0.187 [0.200]	0.187 [0.203]	0.187 [0.189]	0.187 (0.166)	0.187* (0.111)
Observations	5,850	5,850	5,850	5,850	5,850	5,850	5,850
<b>Panel D: Effect on Implementation Efficiency (RD Estimates)</b>							
Outcome: Productivity							
Newstate × Post	0.319** (0.140)	0.319** [0.136]	0.319** [0.135]	0.319** [0.133]	0.319** [0.130]	0.319*** (0.112)	0.319*** (0.0820)
Observations	3,345	3,345	3,345	3,345	3,345	3,345	3,345
Outcome: Cost Efficiency							
Newstate × Post	0.0784*** (0.0263)	0.0784** [0.0335]	0.0784** [0.0374]	0.0784** [0.0365]	0.0784** [0.0343]	0.0784*** (0.0288)	0.0784*** (0.0204)
Observations	3,345	3,345	3,345	3,345	3,345	3,345	3,345

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level in the baseline specification in column 1. Conley Standard Errors (in square brackets) for varying spatial correlation distance cutoffs are reported in columns 2 - 5. Standard errors (in parentheses) are clustered at the grid-level (approx. 10 km × 10 km) in column 6 and at the grid - district - pair level in column 7. DiDC estimates are reported in all columns of Panels A - C. DiDC specifications in Panels A - C include pair-period FEs. RD estimates are reported in all columns of Panel D. RD specifications in Panel D include pair FEs. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A5: Robustness to Different Forms of Single-Dimensional RD Polynomials**

Bandwidth:	Linear Polynomial in Distance to Stateborder			Quadratic Polynomial in Distance to Stateborder			Interacted Quadratic Polynomial in Distance to Stateborder		
	60 km	50 km	40 km	All Villages in Border-Districts	110 km	85 km	All Villages in Border-Districts	110 km	85 km
	(1)	(2)	(3)		(4)	(5)		(6)	(7)
Panel A: Effect on Nighttime Lights Density									
Outcome: Avg. Level of Lights Density									
Newstate × Post	1.430*** (0.306)	1.240*** (0.334)	0.923** (0.350)	1.831*** (0.271)	1.820*** (0.283)	1.712*** (0.303)	1.342*** (0.316)	1.010*** (0.308)	0.687** (0.303)
Observations	28,696	24,942	20,084	40,940	39,724	36,264	40,940	39,724	36,264
Panel B: Effect on Firm-Level Activity and Non-Farm Employment									
Outcome: Firms (All)									
Newstate × Post	27.40*** (8.986)	29.20*** (10.74)	30.89** (12.36)	19.66*** (5.684)	22.01*** (6.672)	25.87*** (8.584)	33.06*** (12.51)	36.71** (15.41)	40.05** (17.86)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Firms (Pvt)									
Newstate × Post	26.80*** (8.756)	28.85*** (10.50)	30.87** (12.11)	18.79*** (5.494)	21.24*** (6.420)	25.25*** (8.270)	32.68*** (12.09)	36.53** (14.97)	40.35** (17.45)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Firms (Gov)									
Newstate × Post	0.596 (0.558)	0.358 (0.584)	0.0135 (0.631)	0.874* (0.504)	0.774 (0.545)	0.626 (0.607)	0.382 (0.693)	0.186 (0.740)	-0.302 (0.726)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Non-Farm Emp.									
Newstate × Post	73.47*** (23.65)	79.20*** (28.00)	84.51*** (31.66)	55.53*** (16.45)	61.60*** (18.78)	69.52*** (23.29)	86.99*** (32.29)	93.32** (39.00)	101.0** (44.78)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Mfg. Emp.									
Newstate × Post	3.685** (1.683)	3.456* (1.848)	3.896** (1.522)	5.798*** (1.920)	4.729** (1.932)	3.305 (2.016)	1.691 (2.349)	1.011 (2.664)	2.170 (2.560)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Ind. Emp.									
Newstate × Post	3.928** (1.882)	4.997** (2.362)	4.835** (1.899)	6.178*** (2.086)	4.807** (2.072)	2.647 (2.213)	1.387 (2.559)	0.779 (2.829)	3.172 (2.828)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. DiDC estimates are reported in all columns of Panels A - C. RD estimates are reported in all columns of Panel D. All coefficients are estimated using the respective RD polynomial and bandwidth. Columns 1 - 3 are estimated using a linear polynomial in distance to stateborder, columns 4 - 6 are estimated using a quadratic polynomial in distance to stateborder, and columns 7 - 9 are estimated using an interacted quadratic polynomial in distance to stateborder.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A5 (Continued): Robustness to Different Forms of Single-Dimensional RD Polynomials**

Bandwidth:	Linear Polynomial in Distance to Stateborder			Quadratic Polynomial in Distance to Stateborder			Interacted Quadratic Polynomial in Distance to Stateborder		
	60 km	50 km	40 km	All Villages in Border-Districts	110 km	85 km	All Villages in Border-Districts	110 km	85 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<b>Panel C: Effect on Delivery of Public Goods</b>									
Outcome: Schools									
Newstate × Post	0.0644 (0.0437)	0.0893** (0.0443)	0.0566 (0.0568)	0.0677** (0.0287)	0.0860** (0.0306)	0.0980** (0.0351)	0.109** (0.0472)	0.106* (0.0539)	0.0998 (0.0618)
Observations	7,820	6,642	5,494	11,320	11,004	10,162	11,320	11,004	10,162
Outcome: Health Cntr.									
Newstate × Post	0.339*** (0.108)	0.331*** (0.115)	0.309** (0.134)	0.328*** (0.0929)	0.330*** (0.0957)	0.358*** (0.0985)	0.365*** (0.118)	0.406*** (0.133)	0.394*** (0.149)
Observations	22,014	19,062	15,546	31,684	30,594	27,884	31,684	30,594	27,884
Outcome: Telephone									
Newstate × Post	0.0341 (0.0606)	0.0674 (0.0661)	0.0745 (0.0755)	-0.0181 (0.0462)	-0.0196 (0.0485)	0.00912 (0.0500)	0.0319 (0.0642)	0.0654 (0.0693)	0.113 (0.0741)
Observations	22,474	19,478	15,896	32,274	31,168	28,424	32,274	31,168	28,424
Outcome: Power									
Newstate × Post	0.518*** (0.115)	0.462*** (0.135)	0.599*** (0.121)	0.433*** (0.111)	0.481*** (0.124)	0.485*** (0.138)	0.566*** (0.169)	0.457** (0.176)	0.253* (0.134)
Observations	7,126	5,850	4,268	10,392	10,278	9,738	10,392	10,278	9,738
<b>Panel D: Effect on Implementation Efficiency</b>									
Outcome: Productivity									
Newstate	0.338** (0.133)	0.317** (0.142)	0.329** (0.136)	0.300** (0.122)	0.256** (0.124)	0.256** (0.126)	0.215 (0.148)	0.276* (0.145)	0.310** (0.143)
Observations	3,656	3,345	2,851	4,875	4,675	4,278	4,875	4,675	4,278
Outcome: Cost Efficiency									
Newstate	0.0715** (0.0254)	0.0784** (0.0262)	0.0643** (0.0301)	0.0707*** (0.0214)	0.0612** (0.0220)	0.0579** (0.0251)	0.0527 (0.0318)	0.0649* (0.0331)	0.0761** (0.0338)
Observations	3,656	3,345	2,851	4,875	4,675	4,278	4,875	4,675	4,278

*Notes*: Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. DiDC estimates are reported in all columns of Panels A - C. RD estimates are reported in all columns of Panel D. All coefficients are estimated using the respective RD polynomial and bandwidth. Columns 1 - 3 are estimated using a linear polynomial in distance to stateborder, columns 4 - 6 are estimated using a quadratic polynomial in distance to stateborder, and columns 7 - 9 are estimated using an interacted quadratic polynomial in distance to stateborder.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A6: Robustness to Different Forms of Multi-Dimensional RD Polynomials**

Bandwidth:	Linear Polynomial in Latitude and Longitude			Quadratic Polynomial in Latitude and Longitude			Cubic Polynomial in Latitude and Longitude		
	60 km	50 km	40 km	All Villages in Border-Districts	110 km	85 km	All Villages in Border-Districts	110 km	85 km
	(1)	(2)	(3)		(4)	(5)		(6)	(7)
<b>Panel A: Effect on Nighttime Lights Density</b>									
Outcome: Avg. Level of Lights Density									
Newstate × Post	1.563*** (0.278)	1.539*** (0.282)	1.530*** (0.281)	1.611*** (0.289)	1.619*** (0.300)	1.502*** (0.317)	1.414*** (0.291)	1.319*** (0.282)	1.203*** (0.273)
Observations	28,696	24,942	20,084	40,940	39,724	36,264	40,940	39,724	36,264
<b>Panel B: Effect on Firm-Level Activity and Non-Farm Employment</b>									
Outcome: Firms (All)									
Newstate × Post	20.78*** (5.517)	21.16*** (5.742)	22.32*** (6.050)	20.43*** (5.645)	21.97*** (6.433)	23.82*** (7.793)	23.41*** (7.081)	23.80*** (7.450)	25.24*** (8.007)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Firms (Pvt)									
Newstate × Post	20.37*** (5.206)	20.82*** (5.421)	21.97*** (5.695)	19.70*** (5.326)	21.28*** (6.053)	23.23*** (7.348)	23.00*** (6.742)	23.34*** (7.088)	24.78*** (7.624)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Firms (Gov)									
Newstate × Post	0.410 (0.530)	0.340 (0.537)	0.355 (0.554)	0.737 (0.559)	0.699 -0.6	0.584 (0.647)	0.405 (0.573)	0.456 (0.595)	0.467 (0.603)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Non-Farm Emp.									
Newstate × Post	50.26*** (13.99)	50.65*** (14.46)	52.89*** (15.08)	52.62*** (15.58)	55.88*** (17.37)	57.82*** (20.38)	56.10*** (18.04)	55.63*** (18.56)	58.20*** (19.86)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Mfg. Emp.									
Newstate × Post	5.649*** (1.399)	5.774*** (1.405)	5.108*** (1.275)	5.473*** (1.391)	4.158*** (1.403)	2.329 (1.611)	4.449*** (1.523)	3.729** (1.455)	2.842* (1.544)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736
Outcome: Ind. Emp.									
Newstate × Post	4.728*** (1.697)	5.041*** (1.747)	4.727*** (1.595)	5.356*** (1.678)	3.756** (1.625)	1.454 (1.754)	3.681** (1.671)	2.966* (1.601)	2.158 (1.649)
Observations	18,932	16,388	13,292	27,290	26,278	23,736	27,290	26,278	23,736

*Notes* : Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. DiDC estimates are reported in all columns of Panels A - C. RD estimates are reported in all columns of Panel D. All coefficients are estimated using the respective RD polynomial and bandwidth. Columns 1 - 3 are estimated using a linear polynomial in latitude and longitude, columns 4 - 6 are estimated using a quadratic polynomial in latitude and longitude, and columns 7 - 9 are estimated using a cubic polynomial in latitude and longitude.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A6 (Continued): Robustness to Different Forms of Multi-Dimensional RD Polynomials**

Bandwidth:	Linear Polynomial in Latitude and Longitude			Quadratic Polynomial in Latitude and Longitude			Cubic Polynomial in Latitude and Longitude		
	60 km	50 km	40 km	All Villages in Border-Districts	110 km	85 km	All Villages in Border-Districts	110 km	85 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<b>Panel C: Effect on Delivery of Public Goods</b>									
Outcome: Schools									
Newstate × Post	0.0617** (0.0235)	0.0563** (0.0218)	0.0529** (0.0217)	0.0668** (0.0260)	0.0804** (0.0260)	0.0836** (0.0286)	0.0698** (0.0276)	0.0658** (0.0279)	0.0705** (0.0273)
Observations	7,820	6,642	5,494	11,320	11,004	10,162	11,320	11,004	10,162
Outcome: Health Cntr.									
Newstate × Post	0.252*** (0.0941)	0.257*** (0.0952)	0.290*** (0.0954)	0.311*** (0.0901)	0.322*** (0.0897)	0.358*** (0.0884)	0.340*** (0.0848)	0.357*** (0.0837)	0.372*** (0.0823)
Observations	22,014	19,062	15,546	31,684	30,594	27,884	31,684	30,594	27,884
Outcome: Telephone									
Newstate × Post	0.0605 (0.0519)	0.0602 (0.0525)	0.0766 (0.0524)	0.00961 (0.0512)	0.0103 (0.0545)	0.0559 (0.0544)	0.0461 (0.0566)	0.0526 (0.0570)	0.0850 (0.0535)
Observations	22,474	19,478	15,896	32,274	31,168	28,424	32,274	31,168	28,424
Outcome: Power									
Newstate × Post	0.408*** (0.0843)	0.402*** (0.0943)	0.362*** (0.0881)	0.452*** (0.108)	0.510*** (0.116)	0.499*** (0.115)	0.368*** (0.0890)	0.359*** (0.0899)	0.341*** (0.0914)
Observations	7,126	5,850	4,268	10,392	10,278	9,738	10,392	10,278	9,738
<b>Panel D: Effect on Implementation Efficiency</b>									
Outcome: Productivity									
Newstate	0.122 (0.0865)	0.101 (0.0862)	0.0997 (0.0851)	0.125 (0.107)	0.101 (0.106)	0.119 (0.104)	0.0813 (0.101)	0.0876 (0.0948)	0.0808 (0.0895)
Observations	3,656	3,345	2,851	4,875	4,675	4,278	4,875	4,675	4,278
Outcome: Cost Efficiency									
Newstate	0.0582** (0.0204)	0.0600** (0.0210)	0.0600** (0.0208)	0.0573** (0.0218)	0.0472** (0.0213)	0.0317 (0.0232)	0.0483* (0.0264)	0.0514* (0.0276)	0.0520* (0.0303)
Observations	3,656	3,345	2,851	4,875	4,675	4,278	4,875	4,675	4,278

*Notes* : Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. DiDC estimates are reported in all columns of Panels A - C. RD estimates are reported in all columns of Panel D. All coefficients are estimated using the respective RD polynomial and bandwidth. Columns 1 - 3 are estimated using a linear polynomial in latitude and longitude, columns 4 - 6 are estimated using a quadratic polynomial in latitude and longitude, and columns 7 - 9 are estimated using a cubic polynomial in latitude and longitude.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A7: DiD and DiDC Estimates with Nighttime Lights Outcome Variable Constructed in Different Ways**

Dep. Variable:	Sample <i>includes</i> areas without inhabitation				Sample <i>excludes</i> areas without inhabitation				Main Specification			
	Adding 1	Adding Min. NTL	Adding 0.01	Prob. Unit is Lit	Adding 1	Adding Min. NTL	Adding 0.01	Prob. Unit is Lit	Adding 1	Adding Min. NTL	Adding 0.01	Prob. Unit is Lit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: DiD (Sample - All Villages in Border-Districts)												
Newstate × Post	0.496*** (0.0811)	1.823*** (0.297)	1.543*** (0.251)	0.233*** (0.0383)	0.495*** (0.0810)	1.819*** (0.296)	1.539*** (0.251)	0.233*** (0.0381)	0.584*** (0.0524)	2.157*** (0.192)	1.824*** (0.163)	0.276*** (0.0249)
Observations	24,600	24,600	24,600	24,600	23,832	23,832	23,832	23,832	40,940	40,940	40,940	40,940
Pair-Period FEs	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
Panel B: DiDC (Sample - Villages within 50 km from Border)												
Newstate × Post	0.298** (0.128)	1.412** (0.544)	1.168** (0.453)	0.204** (0.0757)	0.305** (0.128)	1.446** (0.549)	1.196** (0.457)	0.208*** (0.0765)	0.261*** (0.0843)	1.301*** (0.350)	1.071*** (0.292)	0.192*** (0.0481)
Observations	13,556	13,556	13,556	13,556	13,056	13,056	13,056	13,056	24,942	24,942	24,942	24,942
Pair-Period FEs	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES

*Notes* : Standard errors (in parentheses) are clustered at the subdistrict level in columns 1 - 8 and at the subdistrict - district - pair level in columns 9 - 12. Panel A reports DiD estimates based on a sample of all villages in border-districts. Panel B reports DiDC estimates based on a sample of villages within 50 km from the CH-MP border. Specifications in columns 1 - 8 do not include pair-period FEs i.e., a village  $v$  near the border appears only once in our sample. Coefficients in columns 9 - 12 are estimated using our main DiD and DiDC specifications respectively (with pair-period FEs). Specifications in columns 1 - 4 *include* areas without inhabitation while specifications in columns 5 - 8 *exclude* areas without inhabitation. A constant of 1 is used in the natural log transformation of nighttime lights density in specifications in columns 1, 5, and 9. The smallest non-zero value of nighttime lights density (0.0029985) is used as the constant in the natural log transformation of nighttime lights density in specifications in columns 2, 6, and 10. A constant of 0.01 is used in the natural log transformation of nighttime lights density in specifications in columns 3, 7, and 11. All columns except 4, 8, and 12 use the average level of nighttime lights density as the outcome variable. An indicator variable for whether the unit (village in our case) is lit is used as the dependent variable in specifications in columns 4, 8, and 12. This indicator variable takes a value of 1 if the nighttime lights density of a unit is non-zero and a value of 0 if the nighttime lights density of a unit is zero.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Table A8: Robustness to Top-Coding (using Zhao et al. (2022) Data) and Overflow and Blooming (Donut Exercise)**

Specification:	Using Zhao et al. (2022) Data		Donut Exercise	
	DiD	DiDC	DiD	DiDC
Sample:	All Villages in Border-Districts	Villages within 50km from Border	All Villages in Border-Districts	Villages within 50km from Border
	(1)	(2)	(3)	(4)
	Dep. Var: Avg. Level of Lights Density			
Newstate	0.203 (0.246)	-0.138 (0.321)	0.159 (0.259)	-0.297 (0.413)
Newstate × Post	1.658*** (0.143)	1.001*** (0.256)	1.910*** (0.165)	1.447*** (0.312)
Observations	40,940	24,942	38,654	22,656

*Notes:* Standard errors (in parentheses) are clustered at the subdistrict - district - pair level. DiD estimates for a sample of all CH and MP villages in border-districts are reported in columns 1 and 3 while DiDC estimates for a sample of villages within 50 km from the CH-MP border are reported in columns 2 and 4. Coefficients in columns 1 and 2 are estimated using Zhao et al. (2022) data. Estimates in columns 3 and 4 are based on a sample that excludes villages within 5 km from the CH-MP border on either side. Specifications in all columns use the average level of nighttime lights density as the outcome variable. Specifications in all columns include pair-period FEs.

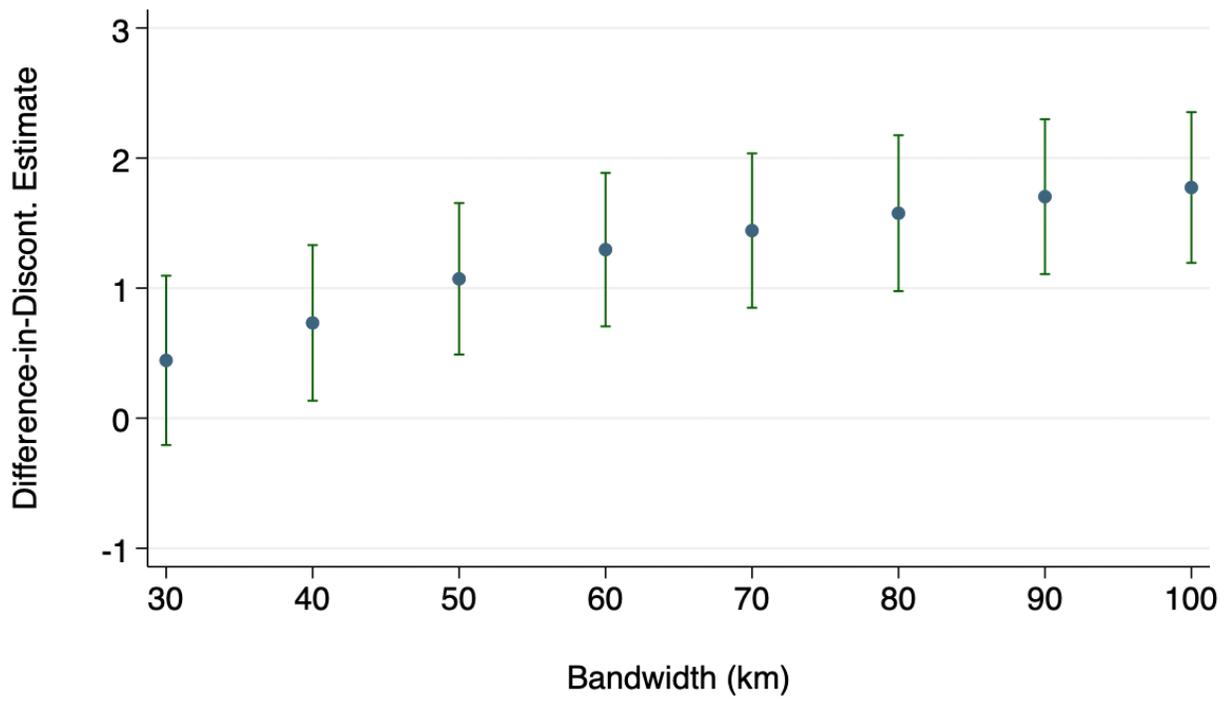
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A9: Placebo Split (Mechanism Analysis - Political Accountability and Government Responsiveness)**

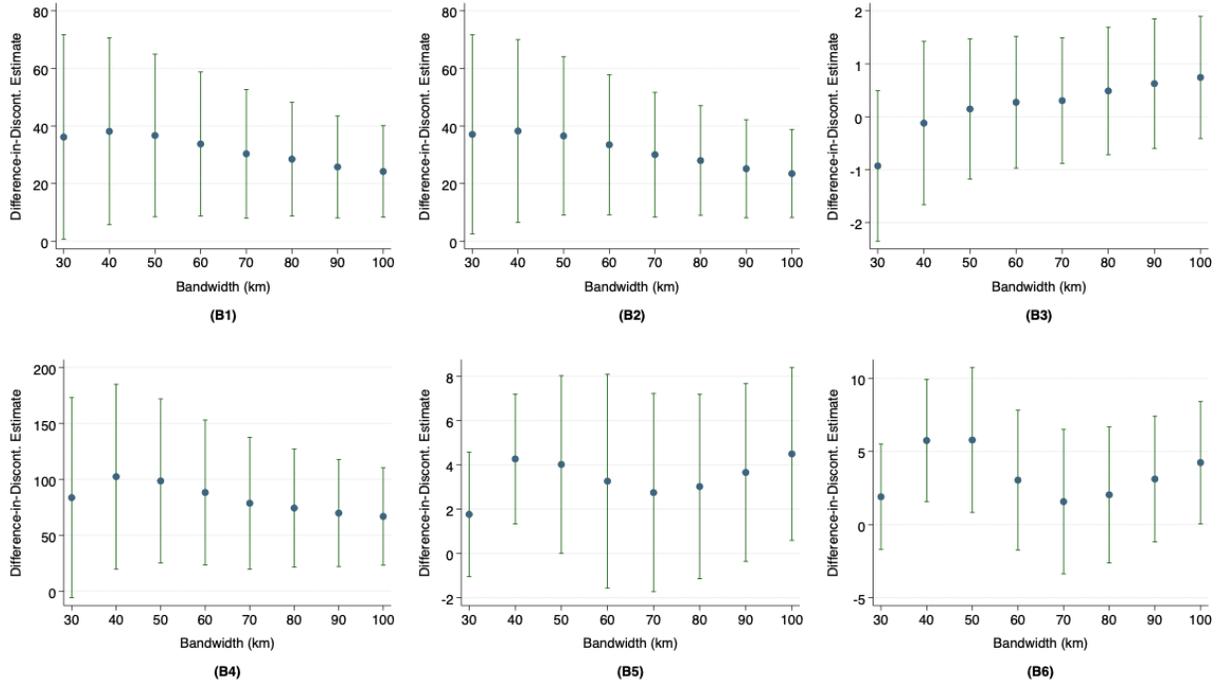
Dep. Var:	Sample: All Constituencies in CH and MP		Sample: All Constituencies in Border-Districts	
	Voter Turnout	Inv. Win Margin	Voter Turnout	Inv. Win Margin
	(1)	(2)	(3)	(4)
Newstate	-0.0330 (0.0230)	-0.0293** (0.0146)	0.0235 (0.0415)	-0.0396 (0.0253)
Newstate × Post	0.0307** (0.0135)	0.0271 (0.0177)	-0.00963 (0.0277)	0.0316 (0.0399)
Observations	952	952	279	279
Pair-Period FEs	NO	NO	YES	YES

*Notes* : Standard errors (in parentheses) are clustered at the district level in columns 1 and 2 and at the district - pair level in columns 3 and 4. DiD placebo estimates in columns 1 and 2 are based on a sample of elections held in all state-legislative assembly constituencies of CH and MP. DiD placebo estimates in columns 3 and 4 are based on a sample of elections held in constituencies in border-districts along CH-MP border. We use measures of political accountability and government responsiveness, specifically voter turnout ratio (columns 1 and 3) and inverse of the win margin (columns 2 and 4), as dependent variables. Since we assume placebo bifurcation happened in 1993, these variables are computed using data for State-legislative elections held before (1985, 1990) and after the placebo bifurcation (1998) in CH and MP.

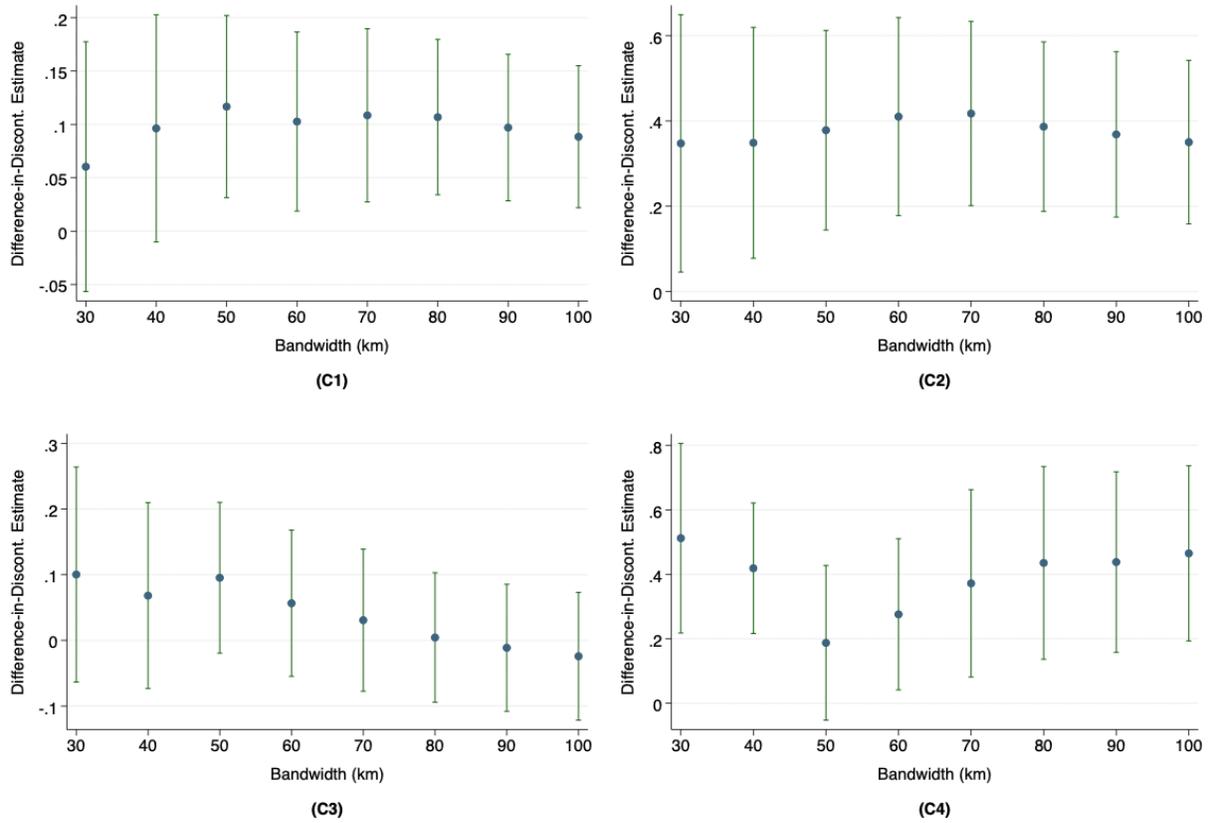
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1



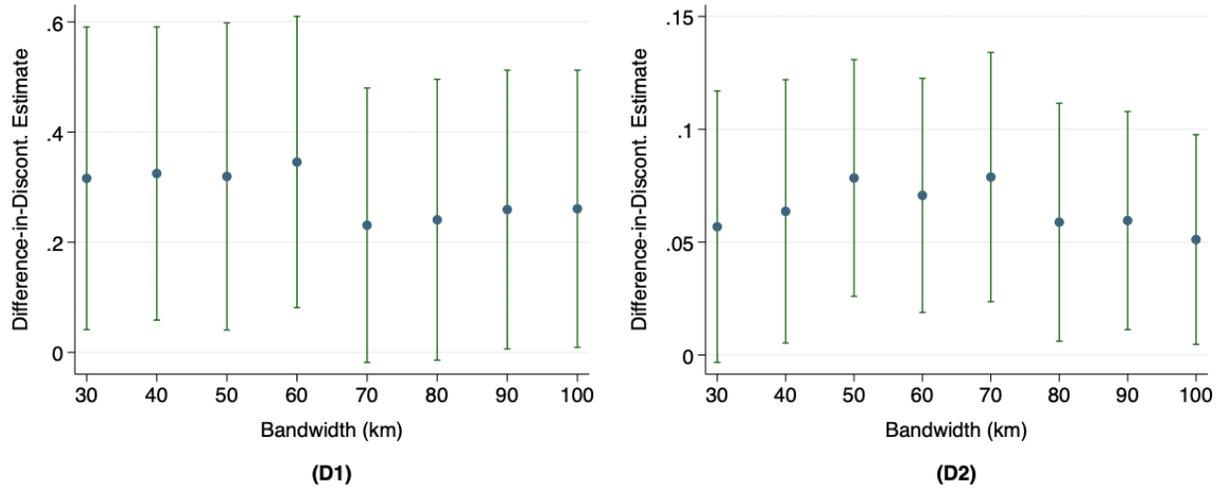
**Figure A1.A:** DiDC Estimates for a range of bandwidths with Nighttime Lights Density as the outcome variable.



**Figure A1.B:** DiDC Estimates for a range of bandwidths with total number of firms (**B1**), number of private firms (**B2**), number of government firms (**B3**), total non-farm employment (**B4**), manufacturing employment (**B5**), and industrial employment (**B6**) as the outcome variables.



**Figure A1.C:** DiDC Estimates for a range of bandwidths with measures of public goods, specifically the change in proportion of villages that have a middle school (C1), healthcare center (C2), telephone connection (C3), and power for all purposes (C4), as the outcome variables.



**Figure A1.D:** DiDC Estimates for a range of bandwidths with measures of state's efficiency in implementing government programs, specifically the natural log of average productivity (average rate of new road construction) **(D1)** and the natural log of average cost efficiency (ratio of stipulated to actual cost) **(D2)** of new road construction projects between 2001 and 2015, as the outcome variables.