Distributing Power: Public Service Provision to the Poor in India

Brian Min *
Ph.D. candidate
Department of Political Science
University of California, Los Angeles
4284 Bunche Hall, Los Angeles, CA 90095
Email: bmin@ucla.edu

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Abstract

How do governments distribute basic public services when budget constraints necessitate their rationing? This paper examines variations in the distribution of scarce electrical power in northern India over the last two decades. Drawing on a novel set of satellite imagery of the earth at night that avoids the biases and missing data problems affecting traditional measures, I construct annual indicators of electrification for all 98,000 villages in Uttar Pradesh. By observing temporal variations in nighttime light output at the village level over three election cycles, I use matching and multilevel models to show that representation by a low-Caste party increases electrification rates in India's villages.

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1 Introduction

How do governments apportion basic public services when budget constraints necessitate their rationing? The way states respond to this question has profound implications for patterns of poverty and regional inequality. Especially in the developing world, whether or not one has access to electricity, clean water, or education is largely determined by the choices of governments and their agents. While there is a long theoretical tradition extolling the virtues of democracy for development, a growing body of research has challenged the effectiveness of democracies in meeting the needs of the poor, often because electoral politics are compromised by clientelism, patronage, or ethnic favoritism.

This paper engages this critical debate by examining the provision of scarce electrical power in northern India over the last two decades at an unprecedented level of geographic precision. More people in India lack electricity than any other country in the world, and nowhere more so than in the state of Uttar Pradesh where an estimated 60 million people have no electrical connection at home. Even for those fortunate to be on the grid, power cuts are ubiquitous and unpredictable, imposing enormous costs to both citizens and businesses. More than simply a modern convenience, access to electricity is a life-altering transformation that improves quality of life and enables economic development. Electric light extends a day's productive hours, allowing children to study after the sun has set, and enhancing safety at night. Powered water pumps reduce the effort needed to collect clean water. Refrigeration allows for the preservation of food and medicines. Yet Uttar Pradesh lacks the electricity supply to provide to all who need or want it, and thus its distribution is heavily rationed.

Given its scarcity and high value, how do governments decide who gets electrical power and who does not? Answering this question is difficult because most existing data on electricity provision is highly aggregated or lack comparability across space and time. I overcome these challenges by using a novel set of satellite imagery to identify levels and changes in electricity provision at the village-level in Uttar Pradesh from 1992 to 2003. By using nighttime light output as an indicator of electricity availability and consumption, I construct annual indicators of electrification for all 98,000 villages, providing up to 1.2 million village-year observations. The timeframe of my analysis captures a period of dramatic social change and observes the results of intensely contested state elections, especially between the powerful right-wing Bharatiya Janata Party (BJP) and the emergent low-Caste Bahujan Samaj Party (BSP), whose core support lies primarily among poor and rural Scheduled Caste (SC) voters. Drawing on the full set of village observations and controlling for a rich array of village- and constituency-level covariates, I show that villages in State Assembly constituencies represented by the low-Caste BSP were significantly more likely to be electrified than those represented by the BJP and other parties.

However, direct analysis of observational data do not easily reflect causal effects, since that requires the evaluation of a counterfactual: would a village's electrification status change if it had been represented by another party rather than the BSP? I attempt to get closer to the true causal effects of BSP representation by focusing on a subset of villages around the pivotal 2002 state election in which power shifted from the right-wing BJP to the low-Caste BSP. Exploiting the abundance of data, I use matching techniques to identify similar villages that differ only on whether they switch to BSP representation or retained BJP representation. Based on multilevel regression analysis of the matched data, I show a strong positive treatment effect of BSP representation on the probability of village electrification. I also investigate which villages are targeted with new electrification and find that villages with a large surplus of core BSP supporters are significantly *less* likely to benefit from new electricity than villages with many swing voters.

This study, while focused on a single region over a limited time period, speaks to larger questions in the literature on public service provision and democracy. How do democratically elected leaders distribute local public goods when it must choose between investing in high-productivity growth areas or diverting scarce resources towards rural areas where voters are numerous? Does democracy create strong enough incentives for the delivery of public services to the poor? Do democratic governments distribute universally or do they target core or swing voters?

A generation of theorists have lauded the positive effects of democracy on the provision of public goods. The conventional wisdom holds that democracies provide more public services because basic services like electricity, water, and sanitation are highly valued by the poor. Since the typical median voter is poor, election results should reflect a preference for higher public services (Meltzer & Richard 1981, Wittman 1989, Gradstein 1993). A similar theme is echoed by Acemoglu & Robinson (2006, p. 18) who state, "nondemocracy is generally a regime for the elite and the privileged; comparatively, democracy is a regime more beneficial to the majority of the populace, resulting in policies relatively more favorable to the majority." Anecdotal observations — like Amartya Sen's (1999) famous claim that famines do not occur in democracies — and some empirical studies have supported this expectation (Lake & Baum 2001, Bueno de Mesquita et al. 2003). But if democracies are better at providing public goods than autocracies, why do 57% of India's citizens lack electricity compared to fewer than 2% in China (International Energy Agency 2002)? Even if we cannot generalize from this paired comparison, there appears to be little cross-national evidence that democracy improves the welfare of the poorest or most vulnerable segments of society (Keefer 2005, Ross 2006). Keefer & Khemani, drawing on experiences in international development, observe that "policymakers in poor democracies regularly divert spending away from areas that most benefit the poor or fail to implement policies that improve the services that are known to disproportionately benefit poor people" (2005, p. 2). Meanwhile, an internal evaluation of 120 World Bank electrification projects, most in democratic states, laments that "the larger share of benefits from rural electrification is captured by the non-poor" (World Bank 2008, p. xv). Some argue that the representative aspects of democracy itself can lead to economic inefficiencies in the public provision of goods and services (Besley & Coate 1998, Robinson & Torvik 2005, Mani & Mukand 2007). Numerous studies suggest that clientelistic and patrimonial practices may corrode the supposed virtues of electoral accountability in both the developing and industrialized worlds (Bratton & van de Walle 1994, Chandra 2004, Stokes 2005, Scheiner 2006, Kitschelt & Wilkinson 2007, Diaz-Cayeros, Magaloni & Estévez Forthcoming).

Underlying this debate are vexing concerns over the quality of cross-national data used in our tests (Behrman & Rosenzweig 1994, Ross 2006, Treier & Jackman 2008). How can we reliably estimate the effects of democracy when public service provision is so poorly measured due to variations in definitions, data-gathering practices, bureaucratic capacity, and possibilities of fraud? In much of the world we simply do not know who gets public services, and reliable data is most scarce precisely where poverty is most persistent. The approach used in this paper harnesses new data collection technologies to confront these difficult challenges.

My research builds upon several empirical studies which statistically evaluate the role of politics on local public goods provision in India. Chhibber & Nooruddin (2004) use state-level data to link variations in public goods provision to the number of effective parties competing in state assembly elections. Banerjee & Somanathan (2007) is the only study that collects data for all villages in

India. However, they aggregate their data into national parliamentary constituencies and test only for the effects of social divisions on public goods provision and do not look at the effects of electoral competitiveness or other political processes. Two recent studies by economists examine the role of local-level councils on the provision of public goods to villages. Foster & Rosenzweig (2004) use a twenty-year panel dataset of 250 villages to measure the effects of local democracy. They find evidence that increases in the share of poor residents lead village councils to invest more heavily in roads, which enhance the welfare of the landless, relative to irrigation facilities, which enhance the welfare of landowners. Drawing on survey data from 500 villages, Besley, Pande & Rao (2007) show that the heads of local-level Panchayat councils (which govern over several villages) exercise substantial political opportunism by directing more public goods projects to their own villages. My research expands considerably upon these efforts by drilling down to the village-level while retaining a large geographic scope encompassing all villages in India's largest state. I also provide new and recent evidence documenting how the rise of India's most prominent low-Caste party has impacted the livelihoods of the rural poor.

The next two sections provide background and context for the politics of electricity in Uttar Pradesh. I then describe my estimation strategy and data before presenting my results.

2 Politics in Uttar Pradesh

Uttar Pradesh (UP) is the most populous state in India. Home to over 190 million people in an area about half the size of California, it has more people than all but four countries in the world. Located in the north of India and spanning much of the fertile plains of the Ganges river, the densely populated state remains predominantly rural, with 80% of the population living in the countryside in some 98,000 villages. With tens of millions of farmers ploughing fields of cereal crops like wheat, rice, and millet, agriculture is the largest economic activity in UP, accounting for nearly half the state product in 1991 and employing nearly three-quarters of workers.

Many of India's most eminent political leaders have their roots in Uttar Pradesh, including India's first Prime Minister, Jawaharlal Nehru and his prominent descendants like current Congress Party president Sonia Gandhi and her son, Rahul Gandhi. Eight of India's fourteen Prime Ministers have come from Uttar Pradesh. The state controls 80 out of 545 seats in the national parliament, nearly double the contingent of the next largest state. Yet despite its size and influential progeny, Uttar Pradesh remains among India's poorest states. It ranks at or near the bottom across a wide range of socio-economic indicators, including per capita income, infant mortality rates, literacy levels, access to medical facilities, teacher-pupil ratios, and electricity use and access (Uttar Pradesh Planning Department 2006). The World Bank estimates that 8% of the world's poor live in Uttar Pradesh alone.[1]

In the first four decades after independence, the Indian National Congress party enjoyed nearly uninterrupted control of UP's *Vidhan Sabha* (Legislative Assembly). It consistently campaigned on a sweeping pro-poor agenda. However, according to many observers, "While socialist rhetoric was used to try to build political capital, policies in favor of the poor were seldom pursued vigorously" (Kohli 2004, p. 258). By the late 1980s, cracks in the Congress's broad umbrella coalition had widened, and its hegemony in Uttar Pradesh deteriorated rapidly (Brass 1994, Hasan 2002). Voters splintered away towards a new crop of political parties with narrower political agendas. Among these new entrants were two lower-Caste parties, the Bahujan Samaj Party (BSP), drawing on the numerical strength of Scheduled Caste voters, especially among the Chamar, and the Samajwadi Party (SP), supported by many Other Backward Class (OBC) and Muslim voters (Duncan 1999, Pai 2002, Jaffrelot 2003, Chandra 2004). In addition, the Bharatiya Janata Party (BJP), a conservative Hindu nationalist party, popular among upper-Caste and middle class voters, emerged as a powerful force in Uttar Pradesh and Indian politics (Hansen 1999). Following Congress's loss of control over the UP state assembly in the 1989 elections, the BJP, BSP and SP emerged as the most powerful parties in the state, jockeying for power during a decade of intense competition and fragile power-sharing coalitions.

The alignment of voters across these new parties reflected an intensifying polarization of politics along Caste lines (Banerjee & Pande 2007). Caste is a system of social stratification that defines individuals along endogamous hereditary lines. Castes, or *jatis*, were traditionally associated with specific occupations and the most ritually unclean jobs were assigned to those with the very lowest social status, variously referred to as Untouchables, *Harijans*, or *Dalits*. Members of these lowest Castes, officially designated Scheduled Castes (SC) according to classifications dating back to British rule, were historically subject to extreme discrimination and segregation (Mendelsohn & Vicziany

[1]Based on an international poverty line of $1.08/person/day in 1993 PPP adjusted prices, 1998 estimates (World Bank 2002, p. i).

1998, Bayly 1999). Though Caste-based discrimination is formally outlawed, wide disparities in social and economic welfare persist: in 2000, rural SC residents were nearly twice as likely to be below the poverty line and 40% more likely to be illiterate than their non-SC counterparts (Gang, Sen & Yun 2008). In Uttar Pradesh, the significant size of both low-Caste and high-Caste groups — 21% of the population are SC and 10% are Brahmin, both high relative to other Indian states[2] — make them electorally significant voting blocs that parties have courted vigorously.

Responding to and nourishing the mobilization of the rural poor throughout the 1990s, successive UP state governments launched efforts to expand social welfare programs and improve public service provision to historically under-privileged communities. Several projects, championed by the BSP and its charismatic leader, Mayawati Kumar, specifically targeted predominantly SC villages and Dalit *bastis* (neighborhoods). As Chief Minister (briefly) in the late-1990s, Mayawati initiated the Ambedkar Village program (*Ambedkar Gram Vikas Yojana*), promising to provide over 11,000 of the poorest villages with electrification, roads, and irrigation. Prominently identified by the erection of statues of the SC hero and architect of the Indian constitution, B.R. Ambedkar, the village program remains one of Mayawati and the BSP's most signature achievements. Indicative of the state's current political climate, her critics have characterized the program as a mismanaged "pet" project, reflecting her "obsession with the Dalit agenda."[3]

The BSP's electoral success grew rapidly throughout the 1990s. Its share of assembly seats rose from 12 out of 425 seats in the 1991 elections to 67, 66, and 98 seats in the 1993, 1996, and 2002 elections respectively.[4] In the 1996 state elections, the BSP won 62% of the Dalit vote, increasing to 69% in the 2002 election.[5] The 2002 election in particular was a landmark contest representing an inflection point in UP politics as the BSP secured more seats than the incumbent BJP which had governed both UP and the national government in Delhi. While no party commanded a clear majority in 2002, the BSP's strength and influence was sufficient to secure the Chief Minister's post for Mayawati in May of that year.

[2]Data from http://censusindia.gov.in/Tables_Published/SCST/scst_main.html and http://www.outlookindia.com/article.aspx?234783

[3]Tripathi, Purnima S., "Mayawati in Deep Trouble," *Frontline*, Volume 19, Issue 19, September 14-27, 2002.

[4]The number of assembly seats in UP was reduced to 403 after the partition of Uttarakhand out of the state in 2000.

[5]Source: Uttar Pradesh Assembly Election Study, CSDS Data Unit, http://www.india-seminar.com/2007/571/571_sanjay_kumar.htm.

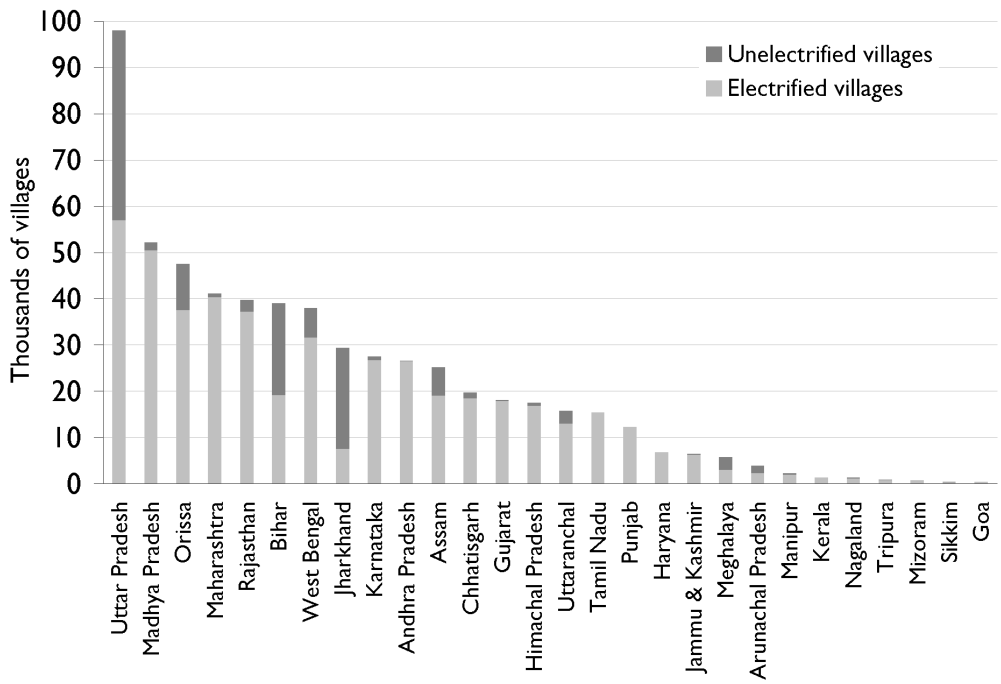


Figure 1: Village electrification rates in Indian states, 2005
Source: Government of India, Ministry of Power.

3 Electricity and the Politics of Distribution

Since at least the time of Gandhi, India has had a longstanding commitment to alleviate poverty, especially in its rural villages where over 70% of Indians live. Yet aggregate levels of public service provision remain low (Kohli 1987, Varshney 1995, Chandra 2004, Chhibber & Nooruddin 2004), including in the provision of electricity. In 2007, peak national demand for electricity outstripped supply by 15%, not even taking into consideration the latent demand from the 600 million Indians who lack a household electrical connection. Striking variations in access persist across the country. According to official Ministry of Power data, less than 60% of Uttar Pradesh's villages were electrified in 2005 compared with well over 90% of villages in the neighboring states of Rajasthan and Madhya Pradesh (see Figure 1). The variation in power access is notable given "the fact that the Indian government, for many years and at all levels, has been explicitly committed to equalizing access to public goods" (Banerjee, Somanathan & Iyer 2005, p. 641).

The power situation in Uttar Pradesh is dismal.[6] Against a typical total available supply of 6,000

[6]Within India's federal structure, electricity distribution and supply is primarily a state-level responsibility, making the state and state-level politics the appropriate level of analysis (Kale 2004).

megawatts, the baseline demand for power is ordinarily around 7,500 megawatts and as high as 9,000 megawatts during peak periods like the Diwali festival. This chronic supply shortage means that roughly 20% to 30% of demand must go unmet, requiring massive and relentless power cuts blacking out huge swaths of the state every day of the year. What electrical power is available is distributed through an intricate network of generating plants, substations, transformers, and thousands of miles of power lines, much of it in disrepair. To protect the fragile power grid, electrical power is rationed across the state through a process guided by formal load-shedding guidelines as well as informal and unscheduled day-to-day adjustments and exceptions to the power delivery schedule.

All electricity transmission, distribution, and supply within the state is managed by the government-operated Uttar Pradesh Power Corporation Limited (UPPCL).[7] The most important distributional decisions regarding how, when, and where power is transmitted across the vast state are centrally executed within a single office at UPPCL, the Central Load Dispatching Station (CLDS). The CLDS monitors the power grid and coordinates the allocation of electrical power across the state via orders to four regional Area Load Dispatch Stations (ALDS) located in Sarnath, Panki, Moradabad, and Meerut. Following instructions from the CLDS, the ALDS in turn make allocations of their limited supply to regional and local electric utilities. Local utilities can make further allocation decisions as necessary, for example, making unscheduled power cuts to certain neighborhoods or villages within their jurisdiction.

Load shedding, or power cuts, affect almost everyone in the state. Official policy dictates anywhere from four hours of daily power cuts in the largest cities to twelve hours of cuts for rural villages. Yet even these minimum targets are usually not met, especially during the hot summer months. In Kanpur, known as the “Manchester of the East” and the state’s largest industrial center, daily power cuts from 9AM to 1PM choke production, shuts down offices and businesses, and leaves schools without lights and homes without fans or refrigeration. Those who can afford it run off of diesel generators and power inverters that store up power overnight, but these alternatives are expensive and not practical for large loads.

A few privileged areas are designated by the state as load shed-free zones and enjoy uninterrupted power supply. This includes the capital city of Lucknow, where power is deemed necessary for the government to function; Agra, home of India’s most important tourist destination, the Taj

[7] It assumed these responsibilities from its predecessor agency, the Uttar Pradesh State Electricity Board, which was unbundled in 2000.

Mahal; and since the 2007 elections, Noida, the technology and outsourcing hub outside New Delhi (incidentally where Mayawati's hometown is located). The prestigious university campuses of Banaras Hindu University and the Indian Institutes of Technology are also exempt from power cuts as are the railways and specially designated industrial zones. Yet even these areas are not immune from the state's power woes. In September 2008, an executive order to impose night-time power cuts on industrial zones was met by outrage and accusations that the Mayawati government was pandering to Muslim voters by attempting to ensure uninterrupted power supply to Muslim localities during the month of Ramadan.[8]

Exemptions to the standard load shedding schedule are made daily. Special allowances are often made for local holidays and festivals, typically as a result of petitions from local leaders. Protection from power cuts are also granted for the Chief Minister, whose travel schedule is communicated to the CLDS.[9] Visits by high level dignitaries like the Indian Prime Minister or foreign heads of state also receive special consideration.

Since electricity is a key input into most productive economic activities, access to electrical power is an important issue for voters. In a 2007 pre-election survey in Uttar Pradesh, nearly four in ten voters noted that development issues including electricity, road, and water concerns were their most important consideration in deciding whom to vote for.[10] Indeed, it is often said that Indian politics comes down to *bijli, sadak, paani* (electricity, roads, water). In the World Bank Enterprise Survey of Indian businesses in 2006, more firms cited access to reliable electricity as the number one obstacle facing their business (35%) than any other concern, including taxes (25%) and corruption (11%). Firms estimated losing 6.6% of sales as a result of power outages with 40% reporting that they owned or shared access to a generator.[11]

Since the provision of electrical power is mediated by politically appointed officials located centrally within arm's reach of the legislative assembly, I hypothesize that the availability of electrical power within different areas of the state should reflect the influence and power of competing political interests. The ability of a small coterie of engineers and power officials to make decisions with such profound effects on access to a critical basic public service creates enormous pressures

[8] Khan, Atiq, "Power supply curtailed for industries in U.P.," *The Hindu*, 8 September 2008

[9] It is often said in Uttar Pradesh that you can tell when the Chief Minister is in town because the power will be working.

[10] `http://www.lokniti.org/pdfs_dataunit/Questionairs/Uttar%20Pradesh%20pre-poll%202007-report.pdf`

[11] World Bank Enterprise Survey, `http://www.enterprisesurveys.org/`

on the office and attracts substantial efforts at political intervention. Engineers at CLDS describe an intricate balancing act in which they must manage competing requests from officials at all levels of influence from across the vast state. In one memorable account, a state assemblyman who had negotiated power cut exemptions from UP's Chief Minister threatened to shoot the CLDS engineer who had turned off the power to his constituency during a severe power crisis.

Substantial anecdotal evidence suggests that politicians routinely interfere in the operation of the state electricity board, from patronage transfers of employees, interventions in the selection of villages for electrification projects, and the assertion of influence on when, where, and how, power cuts are timed and distributed. A Supreme Court-appointed committee diagnosed a culture of political interference in the day-to-day operations of the state electricity board. With the "Board's Chairman and top Executive heads packed by political bosses, the State Government appears to be exercising unbridled power of interference in the day to day working of the Electricity Board. This interference in transfers and postings with political patronage has totally destroyed the autonomous nature of the electricity board..."[12] In a government audit of the Ambedkar Village program, a third of program spending, or $50 million, could not be accounted for, presumably lost to kickbacks and fraud. During the 1997 to 2001 period, the audit revealed that numerous villages had been illegitimately electrified, including six villages in the Barabanki district just east of Lucknow. Several other villages were found to have been selected for electrification by intervention of the Energy Minister, contrary to program guidelines (Wilkinson 2006).

Media reports often assume that powerful politicians are the reason why some constituencies enjoy better access to electricity than others. The Samajwadi Party's leader Mulayam Singh Yadav's home village of Saifai in Etawah district is said to enjoy high levels of development, including new highways, a stadium, an airport and a dedicated substation providing a reliable supply of electricity. According to one account, "While all districts in the state, including Lucknow, face severe power cuts, Saifai has been spared. 'We thank the chief minister for uninterrupted power supply,' says Amar Yadav, a resident of the village, which now has a population of about 4,500."[13] Similar stories are alleged regarding the stability of the power supply in Badalpur, the home village of BSP leader Mayawati (affectionately referred to as Behenji by her followers). Following the BSP's surprising majority victory in the 2007 elections, the village pradhan (chief) of Badalpur, Bhim Singh, told

[12] `http://indiankanoon.org/doc/705971/`

[13] Chakraborty, Tapas, "Air and star power for CM village," *The Telegraph*, 5 September 2004

one reporter, “We get just 7 to 8 hours electricity. All of it will change now.” Meanwhile, the newly elected BSP legislator for the district announced,“We will give 24-hour electricity supply to the village as in the previous Behenji regime. All projects announced by Behenji earlier for the village will be revived.”[14]

4 Research Design

Has the rise of the BSP improved the provision of electricity to villages in Uttar Pradesh? To evaluate this question, I compare state assembly election results to village-level observations of electrification status from 1992–2003.[15] I conduct two sets of analyses. The first evaluates party effects using time-series cross-sectional data for all 98,000 villages in Uttar Pradesh over 12 years, a total of nearly 1.2 million village-year observations. While it is straightforward to use pooled cross-sectional data to estimate the conditional probability of being lit in constituencies that voted for the BSP versus those that did not, such cross-sectional analysis alone cannot easily elucidate causal effects. To estimate the causal effect of party treatment requires the evaluation of a counterfactual claim: Would the dark village have been lit if it had voted for a different party? If villages were randomly assigned to BSP treatment, then estimating the causal effect of BSP rule would be easy. Since this is not the case, in the second analysis, I use matching techniques to generate more reliable estimates of the causal effect of BSP representation on the electrification status of villages.

Following standard notation of the Rubin causal model, the causal effect is the difference in potential outcomes under treatment and control, only one of which is observed for each observation. Let Y_{i1} denote the electrification level for village i that switches representation to the low Caste party and Y_{i0} be the electrification level for villages that remain represented by the non-low Caste party. Treatment is denoted, T_i, equaling 1 when i is in the treatment regime and 0 otherwise. The observed outcome for i is $Y_i = T_iY_{i1} + (1-T_i)Y_{i0}$ and thus the treatment effect for i is $\tau_i = Y_{i1} - Y_{i0}$. In experimental settings with perfect randomization, individuals in both treatment and control groups are equally as likely to receive treatment and so estimation of the treatment effect is simply the mean difference in observed outcomes between the treatment and control groups. However, in observational settings like that here, treatment is not randomly assigned and treated and control

[14] Sharma, Aman, “Maya magic sweeps Noida,” *Indian Express*, 13 May 2007.
[15] State Assembly elections were held in 1993, 1996, and 2002.

groups are likely to differ along multiple dimensions. If we assume that selection into the treated group depends only on observable covariates X_i, we can estimate the average treatment effect on the treated, or ATT:[16]

$$\tau|(T=1) = E\{E(Y_i|X_i, T_i = 1) - E(Y_i|X_i, T_i = 0)|T_i = 1\} \quad (1)$$

In words, I identify the treatment effect of BSP representation as the expected difference in electrification status between a village that received BSP representation and the expected status of the village had it not received the BSP treatment, conditional on a set of covariates, X.

4.1 Methodological Issues

The unit of analysis is the village, even though the key treatment regarding election of state legislators occurs at the assembly constituency level. The data are therefore structured as hierarchical or multilevel data, in which individual observations are clustered within groups and the key treatment is applied at the group level. An alternative design could aggregate the village observations into constituency-level totals and means. However, using village-level data efficiently uses all the data that is available, enables the detection of heterogeneous effects within constituencies, and helps avoid aggregation problems, including those of ecological inference and the related modifiable areal unit problem.

To account for the grouped nature of the village data, I consider different strategies, using multilevel models where possible (these are computationally intensive), including fixed effects at the constituency-level,[17] or by clustering the standard errors within constituency.

An additional form of non-independence exists among observations across space, particularly among geographically proximate villages. Since the likelihood of electrification depends on proximity to the power grid, a village will be more likely to be electrified where the grid is dense and other villages already have power nearby than in remote villages or those located in areas where the grid is sparse. This spatial dependence or spatial autocorrelation needs to be taken into account to derive

[16] More fully, we make the strong ignorability assumption, which assumes that conditional on X, treatment assignment is unconfounded, $Y_0, Y_1 \perp T|X$, and that there is overlap, $0 < Pr(T = 1|X) < 1$ (Rosenbaum and Rubin 1983).

[17] A significant disadvantage of including constituency-level dummies is that the region fixed effects can only be estimated where there is variation on the dependent variable. Observations in constituencies with no variation are dropped, resulting in missing data.

correct standard errors. Unfortunately, standard methods for controlling for spatial dependence are not tractable for networks as large as that observed here. In the typical approach using Moran's I, a spatial weights matrix is created. This implies working with a matrix of nearly 100,000 $\times$ 100,000 for all of UP's villages, which is not computationally tractable. Moreover, spatial lag models with binary dependent variables do not have closed-form solutions and are difficult to estimate (Ward & Gleditsch 2002).

A simpler solution adopted here is to include controls that relate directly to the extent and density of the electrical grid, including a village's distance from the nearest town (since all towns are connected to the grid) and the sum of all nighttime light emissions within the constituency in the first year of my series, 1992 (which should correlate highly with initial power grid density). The inclusion of fixed effects or the use of multilevel modeling will also help account for unmeasured regional variations in the power grid by allowing the intercepts to vary across constituencies. A shortcoming of these approaches is that unlike spatial lag models which allow the degree of similarity to be measured continuously across all villages, varying-intercept models can only control for fixed spatial autocorrelation across constituencies and not within each constituency.

5 Data

The analysis is based on a large dataset of all 98,000 villages in Uttar Pradesh, structured in village-constituency-year format, with annual indicators of electrification status from 1992–2003. Villages are located within 403 state assembly constituencies. On average, each constituency has 400,000 people, 80% of whom are rural living in some 240 villages. Members are elected directly via a single-member simple-plurality rule and state elections were held in 1993, 1996, and 2002. The complete dataset contains approximately 1.2 million village-year observations, which I use to generate broad descriptive trends before defining much smaller subsamples to investigate the causal effects of BSP representation.

5.1 Dependent Variable: Detecting Electrification from Space

I construct annual indicators of electrification status for all villages using a novel set of satellite imagery of the earth at night. The satellite images come from the Defense Meteorological Satellite

Program's Operational Linescan System (DMSP-OLS), a set of military weather satellites that have been flying since 1970 in polar orbit recording high resolution images of the entire earth each night between 20:00 and 21:30 local time. Captured at an altitude of 830 km above the earth, these images reveal concentrations of outdoor lights, fires, and gas flares at a fine resolution of 0.56 km and a smoothed resolution of 2.7 km. Beginning in 1992, all DMSP-OLS images were digitized, facilitating their analysis and use by the scientific community. While daily images are available, the primary data products used by most scientists are a series of annual composite images. These are created by overlaying all images captured during a calendar year, dropping images where lights are shrouded by cloud cover or overpowered by the aurora or solar glare (near the poles), and removing ephemeral lights like fires and other noise. The result is a series of images of time stable night lights covering the globe for each year from 1992 to 2003 (Elvidge et al. 1997*a*, Imhoff et al. 1997, Elvidge et al. 2001). Since the DMSP program may have more than one satellite in orbit at a time, some years have two annual images created from composites from each satellite, resulting in a total availability of 23 annual composite annual images. Images are scaled onto a geo-referenced 30 arc-second grid (approximately 1 km^2). Each pixel is encoded with a measure of its annual average brightness on a 6-bit scale from 0 to 63. Figure 2 shows an image of 2002 time stable night lights in Uttar Pradesh. The very brightly lit patch in the upper left is New Delhi, with a large drop-off in light output immediately at its border with Uttar Pradesh. Compared with traditional data on energy production and consumption, the satellite images reveal explicitly the geographic distribution of electrical power, providing a clearer picture of the beneficiaries of public infrastructure across space. Moreover, since the satellite images are captured electronically through an automated process with little human intervention, the data have the great virtue of being unbiased, consistent, and complete. Analysis of the set of annual images from 1992–2003 show that most of the variation in light output is cross-sectional, or across constituencies. About 20% of the variance is observed over time within constituencies.

The primary dependent variable is a dichotomous measure indicating whether a village is electrified or not, by which I mean whether a village emits visible night lights as detected by satellite in each year from 1992 to 2003.[18] The emission of light at night reveals both the presence of electri-

[18]While I also compute a continuous measure of total light detected at the village level, I prefer the dichotomous variable, which is less sensitive to variations in the sensitivity of the satellite's recording instruments or variable atmospheric conditions over time.

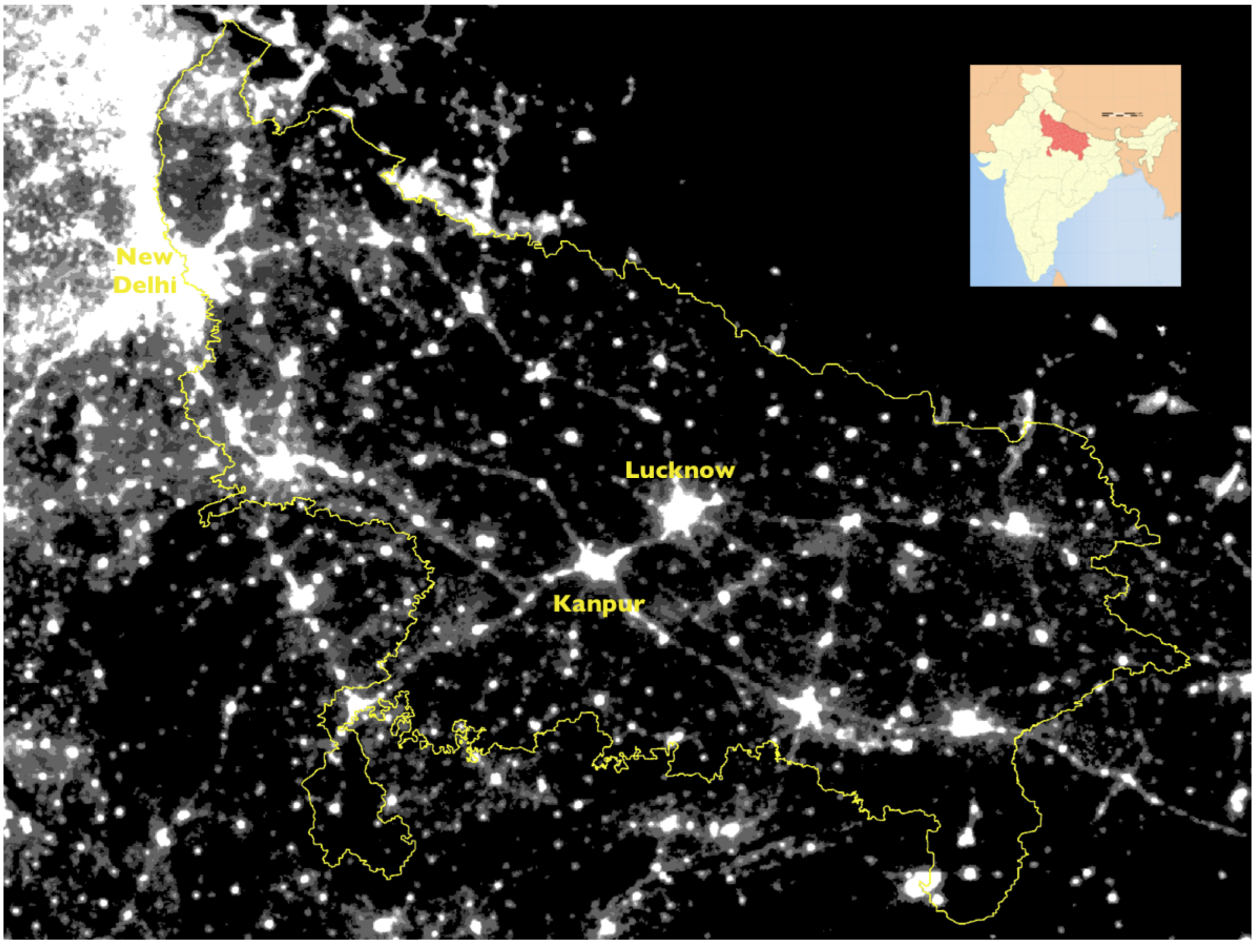


Figure 2: Nighttime lights in Uttar Pradesh, 2002
Image and data processing by NOAA's National Geophysical Data Center.
DMSP data collected by US Air Force Weather Agency.

cal infrastructure *and* the regular flow of electrical power converted into outdoor lighting at night. The ability to detect outdoor lighting is meaningful because it is a useful application of electricity with broad public benefits and suggests contexts in which electricity is generating public goods and positive externalities.

I use GIS software to spatially match and extract average annual nighttime light output for all 98,000 villages in Uttar Pradesh from 1992–2003.[19] I also compute constituency-level measures of total light output by summing the pixel values within each of UP's 403 assembly constituencies in each year. Satellite data are available as annual composites. In years where more than one satellite was in orbit, I average the light pixel values across the two sensors.[20] In each year, I classify all villages with positive non-zero values of light emission as electrified (lit). Since the frequency and intensity of power cuts can vary significantly over time, villages that benefit from a regular provision of electrical power in the evening hours are more likely to appear lit in satellite imagery than a village whose access to power is highly irregular or inconsistent.

Using night lights to detect electrification differs from conventional survey-based approaches or Census definitions which typically ask whether a village or town is connected to the power grid, regardless of whether electricity is actually available or being productively used. Moreover, conventional indicators are usually static, implying that once a village is electrified, it stays electrified. Electrification status measured in these standard ways distorts the actual situation on the ground in much of the developing world, where access to power is often the exception rather than the rule. For citizens, new electric poles and wires are irrelevant if the supply of power is inconsistent or unreliable. As one villager in a newly "electrified" village told me, "We have only had a few hours of power since the men came to install the poles. It is worse now. Now we get a bill even though there is no electricity!"

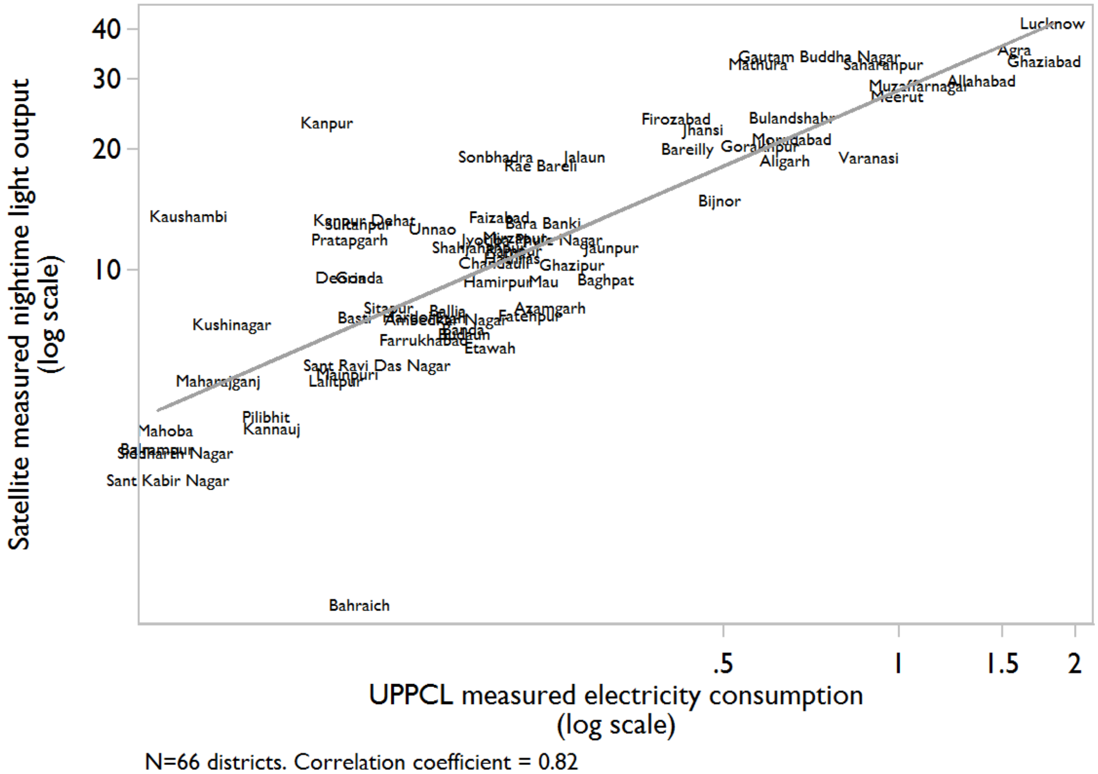
5.1.1 Validating Satellite Imagery as a Measure of Electrification

How reliable are satellite images as an indicator of electricity use? Previous studies have found high correlations between nighttime light output and electricity use at the national level (Elvidge

[19]The village location data are from ML Infomap's VillageMap which provides the point location of all villages in Uttar Pradesh.

[20]The data extraction is performed via a Python script with calls to the geoprocessor object in ArcGIS 9.3. For more info, see "Writing Geoprocessing Scripts," ESRI White Paper, `www.esri.org`.

Figure 3: Comparing satellite-derived and official electricity data, Uttar Pradesh Districts, 2002



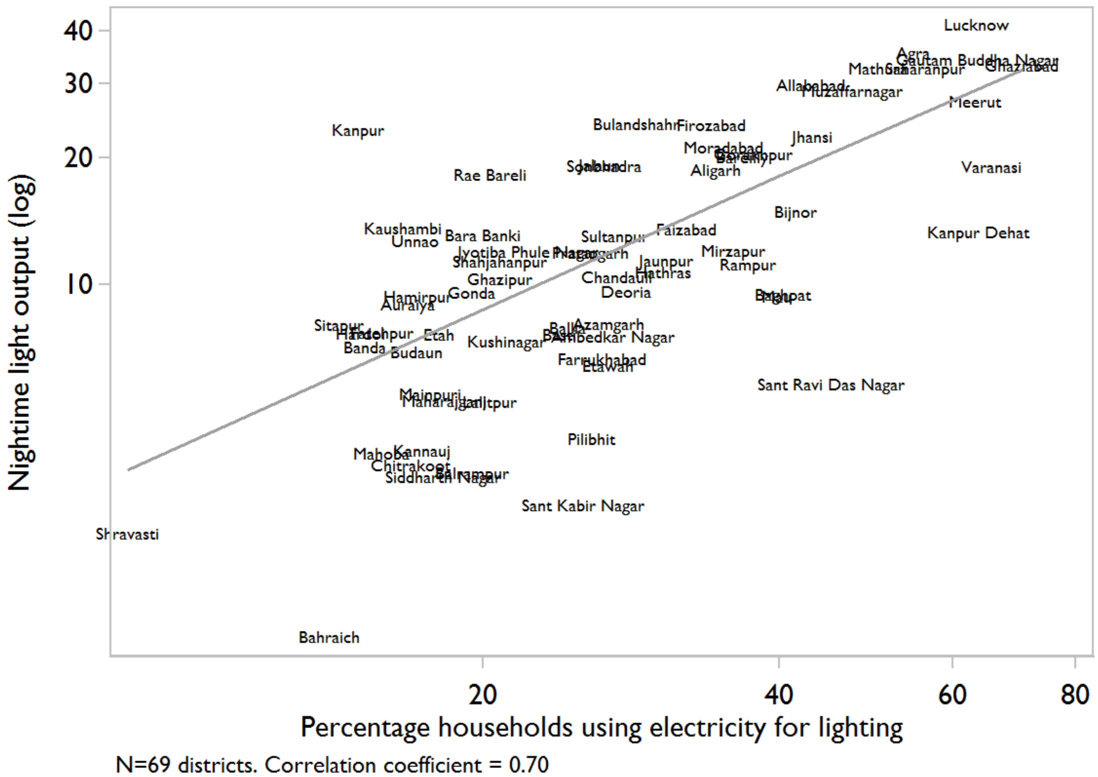
Sources: Author's calculations from DMSP-OLS data; Uttar Pradesh Power Corp.

et al. 1997*b*) but the relationship at smaller sub-national units has not been robustly evaluated. Fortunately, state agencies in India collect an impressive range of electricity data that allow me to show that emission of nighttime lights is indeed a reliable indicator of electricity availability and use, despite some important limitations.

The Uttar Pradesh Power Corporation provided me with monthly reports of electricity consumption for each of its 150 electricity supply zones which I then aggregated up to the district level to enable spatial comparisons against satellite imagery. Figure 3 plots UPPCL's district-level electricity consumption totals against the pixel-by-pixel sum of all light output within each district in 2002. The high correlation between these two sources plausibly suggests a log-linear relationship between electricity provision from the power station and nighttime light emissions detected from space.

How do nighttime lights compare against household electrification rates? Based on 2001 India Census tables, the *Uttar Pradesh Human Development Report* provides estimates at the district level

Figure 4: Comparing satellite data and household electrification rates, Uttar Pradesh Districts, 2001



Sources: Author's calculations from DMSP-OLS data; *2006 Uttar Pradesh Human Development Report*.

of the percentage of households using electricity as the primary source of lighting. These household electrification data are plotted against the total light output within each district in Figure 4. There is again a clear log-linear relationship, though the pattern is noisier than the comparison with energy consumption data.

An alternative government indicator of electrification comes from the Village Amenities database of the Indian Census. The data, collected decennially and most recently in 2001, includes dichotomous indicators of local public goods availability in all villages, including the availability of "power supply" for all 98,000 villages. According to the definition of electrification at the time, any use of electricity, including a single household connection or electrified pumpsets and irrigation, qualified a village as being electrified.[21] About two-thirds of villages also report separate indicators for whether electricity was available for domestic use, agricultural use, or other use.

[21]India's official definition of village electrification was changed in 2005, requiring at least 10% of households to be

Table 1: Village Electrification by Census and by Satellite

	Unlit in Satellite Imagery	Lit in Satellite Imagery	Total
"Power Supply Unavailable" in Census	52.1%	47.9%	100%
"Power Supply Available" in Census	21.3%	78.7%	100%
Total	30.0%	70.0%	100% 97,926 villages

Note: The 2001 Indian Census Village Amenities database reflects reference date of March 31, 1999.

Table 1 presents a contingency table comparing the Census "power supply available" measure against an indicator of visible nighttime lights derived from satellite imagery. Specifically, the village is coded as "lit by satellite" if a positive light value is detected in any annual composite image from 1992–1999. This approach helps avoid excessive false negatives by recognizing that many villages on the power grid appear lit in some years but dark in others, reflecting the large variations in electrical supply and reliability explored here.

By this comparison, 79% of villages are jointly identified as electrified by the Census and satellite imagery. There are a few possible explanations for why villages that are classified as electrified nevertheless appear dark at night. First, because of the expansiveness of the Census's electrification definition, some barely electrified villages might not have the infrastructure or connections to even support a single light. Second, lights from very small or dispersed villages are unlikely to be detected given the limited sensitivity of the satellite sensor.

The detection of villages without power supply availability is much more mixed. Only half of these villages are consistently classified, suggesting that the detection of nighttime lights alone may not reliably indicate that a village is connected to the power grid. Analysis of these villages shows that many unconnected villages that appear lit are close to large towns or urban centers, in which the blooming of city lights spills over the village. Looking only at rural villages located more than 10 km from the nearest town, 62% of these unconnected villages now appear dark. Another possibility is that the emission of nighttime lights reveals the use of privately-owned generators. Fuel-powered

connected and the provision of electricity to public places like schools and the village Panchayat office.

generators are found abundantly across Uttar Pradesh, including in rural roadside markets where power is used to provide basic lighting in stalls. Finally, there may be errors in the Census classifications that contribute to the appearance of Type I and Type II errors. Several media reports have described village residents protesting such incorrect classifications [citation].

In summary, the comparisons suggest that satellite-derived indicators of nighttime lights are a good predictor of standard electricity measures including energy consumption rates, household electrification rates, and village electrification. While the predictions are not perfect, it is not obvious whether this is because of measurement errors in standard indicators or shortcomings of the satellite imagery.

5.2 Independent Variables

The primary variable of interest is a *BSP* party indicator that is coded 1 in years in which a village is represented by a BSP legislator in the State Assembly. The *Scheduled Caste population share* variable codes the proportion of the population classified as Scheduled Caste according to the 2001 Indian Census. Given the very high rates of support for the BSP among SC voters, this variable serves as a proxy for BSP core voters. I create an interaction term *BSP* $\times$ *SC population share* to explore heterogeneous effects of BSP representation depending on the proportion of core voters within a village. Some Assembly Constituency seats are *Reserved* for Scheduled Caste candidates.

To reliably evaluate whether villages under BSP rule were more likely to be electrified and lit, we need to control for factors that might make a village easier to electrify compared to others. For example, very remote villages are more difficult to electrify than one adjacent to a large city. If the kinds of villages that are more likely to be represented by the BSP are systematically different from villages represented by other parties like the BJP, then we need to control for these differences as best as we can. I therefore collect data on a range of village and constituency-level controls.

Village population identifies both the number of potential consumers of electricity in a village and also the number of potential voters. The presence of complementary infrastructure like a *School* or *Medical Facility* in the village might create a higher local demand for electricity, including for lights so students can study, or refrigeration for medicines. Existing infrastructure, as well as the *Literacy Rate* of village residents, may also reflect some latent factor associated with the ability of local residents to secure government projects in their village. *Distance to Nearest Town* is measured in kilometers.

Along with *Paved Approach Road*, these measures provide an indication of remoteness. Since all towns are electrified, this also provides an upper bound estimate of distance to the electric grid.

To account for variations in the level of industrialization and development across the state, *Income Index* is calculated based on the adjusted district per capita income in PPP, scaled to an index between 0 and 1 (Uttar Pradesh Planning Department 2006). The district-level income data are available for 1991 and 2001 for all 70 districts and are the most disaggregated estimates of income of which I am aware. I also compute the log of the total *Light Output* within each constituency in each year. In many models, I include the 1992 value as a proxy indicator for the initial density and capacity of the electrical grid. This is important since future electrification is highly conditional on the extent of the existing electrical grid.

Additional party indicator variables are coded for the *BJP*, *SP*, *Congress*, and all *Other Parties*. To account for serial correlation in a village's electrification status over time, I include a full set of year dummies in all models (Beck, Katz & Tucker 1998).

6 Results and Analysis

6.1 Time-Series Cross-Sectional Analysis

Table 2 shows a set of logit regressions to evaluate party effects on the likelihood that a village will be lit in satellite imagery. To help account for non-independence of village observations within the same constituency, standard errors are clustered at the constituency level.[22]

Model 1 is a reduced model that includes the party dummies, a constituency-level control for the initial income level in 1991, and the constituency's initial nighttime light output in 1992. The Congress Party, which was the hegemonic party in prior decades, is the omitted reference category. The income variable helps account for initial differences in level of economic development. The initial light output measure accounts for existing disparities in electrical infrastructure, the cumulative product of investments made under the former Congress regime. Controlling for these initial regional variations, there are important differences across political parties on the probability that a village within their constituency will be lit. The effects of BSP representation (significant at p=0.06)

[22] The size of the full dataset precludes the use of more sophisticated techniques to account for the grouped nature of the data.

Table 2: Predictors of Village Electrification, 1992–2003

DV is village lit or not	(1)	(2)	(3)	(4)
	Reduced model	Full model	Remote villages only (>10 km from town)	Constituency Fixed Effects
BSP (Bahujan Samaj Party)	0.2275	0.1754	0.2433	0.2045**
	(0.1411)	(0.1376)	(0.2064)	(0.0146)
BJP (Bharatiya Janata Party)	-0.0848	-0.1104	0.1475	-0.0016
	(0.1329)	(0.1269)	(0.1907)	(0.0133)
SP (Samajwadi Party)	0.0994	0.0650	0.0006	-0.0331*
	(0.1288)	(0.1244)	(0.1929)	(0.0133)
Other Party	0.3151*	0.2526	0.2878	0.0245
	(0.1471)	(0.1424)	(0.2089)	(0.0164)
Village-level controls				
Village population (thousands)		0.0682**	0.0599**	0.0515**
		(0.0104)	(0.0135)	(0.0020)
Scheduled Caste population, proportion		0.1579**	0.1446	0.0931**
		(0.0599)	(0.0829)	(0.0119)
Literacy rate in village		2.6076**	3.0227**	1.8015**
		(0.2418)	(0.3004)	(0.0215)
School in village		-0.2530**	-0.2783**	-0.1505**
		(0.0323)	(0.0416)	(0.0057)
Medical facility in village		0.0531	0.0908*	0.0037
		(0.0299)	(0.0409)	(0.0059)
Paved approach road to village		0.3630**	0.3385**	0.2659**
		(0.0273)	(0.0387)	(0.0050)
Distance to nearest town (in km)		-0.0443**	-0.0077	-0.0513**
		(0.0039)	(0.0043)	(0.0004)
Constituency-level controls				
Income index, 1991	-2.2241	-2.3671*	-3.1667*	-4.2079**
	(1.1660)	(0.9715)	(1.2832)	(0.2636)
Nighttime light output in constituency, 1992	1.0689**	0.9854**	1.0351**	1.2470**
	(0.0655)	(0.0611)	(0.0742)	(0.0958)
Reserved constituency		-0.0523	0.0285	2.0709**
		(0.1156)	(0.1376)	(0.3898)
Scheduled Caste population in constituency		-1.1134	-2.3321*	
		(0.9907)	(1.1156)	
Year fixed effects	Yes	Yes	Yes	Yes
AC fixed effects	No	No	No	Yes
Constant	-7.1393**	-7.0442**	-7.8050**	0.2879**
	(0.6341)	(0.6151)	(0.7408)	(0.0608)
Observations	1,171,356	1,171,356	403,212	1,165,644

Constituency-clustered robust standard errors in parentheses.
** p-value $\leq$ .01, two-tailed test. * p-value $\leq$ .05, two-tailed test.

are positive and substantially larger than those of the BJP, SP, or the Congress parties. The large and significant coefficient on Other Party is notable and could indicate the effects of high candidate quality within this group of legislators, a plausible prerequisite for electoral success outside the banner of a mainstream party. (However, the variable is insignificant with the addition of constituency fixed effects. See below).

Controlling for a wide range of additional village- and constituency-level covariates in Model 2 has only a small effect on the party coefficient estimates, with BSP-represented villages still having a higher likelihood of being lit. Model 3 looks only at more remote villages located at least 10 km from the nearest town. This sample, comprising slightly less than half of UP's villages, includes villages whose electrification status are less likely to be affected by the proximity of urban overglow. Among remote villages as well, the positive BSP effect remains visible.

Model 4 adds fixed effects for all 403 constituencies to account for fixed and unobserved factors that may be associated with different patterns of electrification across the state. The fixed effects are significant, suggesting that there are indeed unobserved factors that are omitted from the model. Once these are adjusted for, the effect of BSP representation is now highly significant and represents a much larger positive effect than that of any other party. All other party categories have coefficients close to zero.

These results are notable given the widespread lament in India that all parties have been ineffective in addressing the needs of the poor. When it comes to village electrification, the differences across parties are substantial, and the most positive effects are in villages located in BSP constituencies. However, we cannot easily conclude that these patterns reflect a true causal effect of BSP representation, since it could be biased by an omitted variable in which an unobserved factor is associated with both BSP electoral success *and* higher electrification rates. For example, former Congress party representation might be such a confounder if, in prior decades, the Congress party initiated village electrification projects in locales with large SC populations that later switched support to the BSP in the 1990s. While the inclusion of constituency fixed effects in Model 4 should absorb time-invariant factors that operate within constituencies, and the year dummies should account for broad temporal trends affecting the whole state, these statistical adjustments provide only a partially satisfying response to such concerns. In the next section, I focus on a smaller subset of villages and years and use matching techniques to derive a more compelling estimate of the true causal effect of

BSP representation on the incidence of village electrification.

6.2 Deriving Causal Estimates of BSP Representation on Village Electrification

I focus here on the effects of new BSP representation resulting from the 2002 state elections. This critical election marked an inflection point in the ascendancy of the BSP, demonstrating that it was able to leverage its support among its Scheduled Caste voter base to achieve significant electoral success and compete successfully against India's dominant political parties. At the turn of the century, the BJP had emerged as the most powerful force in Indian politics, controlling both the national government and the state government in UP. Yet the 2002 UP elections dealt a dramatic defeat to the BJP, with its seat share plummeting from 157 seats to 88 seats. For the BSP, whose seat share climbed from 66 to an unprecedented 98 seats, the election was an impressive achievement, subduing skeptics who could not foresee the ascendancy of a party whose support base lay among India's most marginalized citizens. Replacing the BJP leader Rajnath Singh, the BSP's Mayawati was named Chief Minister of UP and served in that post for 16 months from May 2002 through August 2003.[23] Given the dramatic transition in power from BJP to BSP governance during this timeframe, I focus on the period immediately prior to and following the 2002 election to evaluate party effects on changes in village electrification rates.

To define my sphere of analysis, I begin with the 157 assembly constituencies that were represented by the BJP prior to the election. As a result of the election, 37 of these constituencies switched their support to the BSP while 52 retained BJP representation.[24]. Based on this subsample, I ask whether villages in constituencies that switched to BSP representation (the "treatment" group) are more likely to get lit or go dark than if they had retained BJP representation (the "control" group).

I perform two separate analyses within this set of constituencies. First, I evaluate whether unelectrified villages that were *dark* in the year *prior* to the election were more likely to get lit in the year *after* the election, depending on whether they receive the BSP treatment or not. This "Dark Village Sample" is comprised of a treatment group of 2,679 villages spread across 29 constituen-

[23]The 2002 election results were somewhat more complicated than this. The SP won more seats (143) than either the BSP or BJP but was unable to form a government. In a purely opportunistic arrangement, the BJP and BSP formed a tactical alliance with the Chief Minister's office ceded to the BSP. When the alliance collapsed in August 2003, the SP took over the government and its leader, Mulayam Singh, served as Chief Minister until the 2007 election.

[24]For the purposes of this analysis, I ignore BJP constituencies that switch to other parties

cies that switch to BSP representation, and a control group of 3,223 villages in 29 ACs that retain BJP representation. Second, I assess whether lit villages in 2001 were more likely to go dark in 2003, depending on the treatment. In the "Lit Village Sample", the treatment group that switches to BSP representation includes 7,025 villages in 37 constituencies, while the control group has 6,058 villages in 52 constituencies that retain BJP representation.

The contingency tables in Table 3 present a first comparison of the data. Within the Dark Village Sample, 10% of villages that switched to BSP representation in the 2002 election gained light in 2003. That rate was more than twice as high as the electrification rate of villages that retained their BJP representatives. Within the Lit Village Sample, 30% of villages with new BSP representation went dark in 2003, compared with 37% of villages that did not switch and stayed with the BJP. Stepping back for a moment from party effects, the data also show a massive overall decline in the rates of village electrification in 2003 compared with 2001. This is at least partially consistent with UPPCL data showing a decline in electricity production from 2001 to 2003, though the drop in the official data is not nearly as dramatic as that observed by satellite.

The results, while suggestive, will not reflect the true treatment effect so long as treatment and control groups differ systematically across the range of pre-treatment covariates, which is essentially guaranteed since representatives are decided by elections and not by random assignment. To illustrate, Table 4 summarizes the distribution of variables across treatment and control groups within the dark sample.

To address concerns of selection bias and reduce the dependence of results on model specification and parametric assumptions, I use matching in an effort to achieve the highest level of balance across all observed covariates between the treatment and control groups. Matching seeks to make the treated group look as similar as possible to the control group, allowing analysis that is less sensitive to choices of functional form and model selection. By achieving balance, matching reduces model dependence and reduces bias and variance (Ho, Imai, King & Stuart 2007). Having identified a matched sample, I then run analysis to estimate the treatment effect of BSP representation on village electrification rates (for comparative purposes, the Appendix shows the same analysis on the unmatched samples).

To identify matches, I use the genetic search algorithm, GenMatch (Sekhon Forthcoming), which is particularly suited to optimizing balance in contexts where the dimensionality of covariates is

Table 3: Changes in Village Electrification 2001–2003

Dark Sample of Unelectrified Villages in 2001

	RETAINS BJP BJP 2001 → BJP 2003	SWITCHES TO BSP BJP 2001 → BSP 2003	TOTAL
Unlit 2001 → Lit 2003	4.8% 154 villages	**10.1%** **272 villages**	7.2% 426 villages
Unlit 2001 → Unlit 2003	95.2% 3,069	89.8% 2,407	92.8% 5,476
Total	100% 3,223	100% 2,679	100% 5,902

Lit Sample of Electrified Villages in 2001

	RETAINS BJP BJP 2001 → BJP 2003	SWITCHES TO BSP BJP 2001 → BSP 2003	TOTAL
Lit 2001 → Unlit 2003	37.1% 2,248 villages	**30.3%** **2,125 villages**	33.4% 4,373 villages
Lit 2001 → Lit 2003	62.9% 3,810	69.7% 4,900	66.6% 8,710
Total	100% 6,058	100% 7,025	100% 13,083

Table 4: Characteristics of Unlit Villages in Dark Sample, 2001

	RETAINS BJP IN 2002 ELECTION BJP 2001 → BJP 2003 *3,223 villages in* *29 Assembly Constituencies*				**SWITCHES TO BSP IN 2002 ELECTION** BJP 2001 → BSP 2003 *2,679 villages in* *29 Assembly Constituencies*			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Village level variables								
Scheduled Caste population share	0.23	0.19	0	1	0.29	0.22	0	1
Village population (thousands)	1.31	1.26	0.001	11.61	1.39	1.51	0.001	15.54
Village literacy rate	0.35	0.13	0	1	0.40	0.13	0	1
School in village	0.71	0.45	0	1	0.75	0.43	0	1
Medical facility in village	0.27	0.44	0	1	0.25	0.44	0	1
Paved approach road to village	0.52	0.50	0	1	0.51	0.50	0	1
Distance to nearest town (in km)	11.90	9.31	0	105	12.14	10.26	0	99
Assembly Constituency level variables								
Income index (district)	0.40	0.04	0.35	0.50	0.43	0.04	0.37	0.65
2001 total nighttime light output (log)	7.17	0.71	5.44	8.65	7.54	0.54	6.56	9.09
Reserved seat	0.23	0.42	0	1	0.20	0.40	0	1
Avg. Scheduled Caste population share	0.22	0.07	0.10	0.40	0.26	0.05	0.14	0.34

* Uttar Pradesh is comprised of 98,000 villages, 403 state assembly constituencies, and 70 districts.

large. Using one-to-one matching with replacement. I match on the 7 village and 4 constituency-level covariates listed in Table 4, separately for both the Dark and Lit samples. Empirical-QQ plots of all continuous variables in Figure 5 shows substantial improvement in balance after matching, especially on the village-level covariates.

If matching were exact or achieved perfect balance across all covariates (in which all observations would lie on the 45 degree line across all covariates), we could then simply compute the treatment effect by comparing the outcome means across treatment and control groups. This is usually difficult or impossible to achieve in observational settings, including here. As a result, I continue the analysis of the matched sample, conditioning on covariates by estimating multilevel models using random effects logistic regression. The multilevel approach is a preferable strategy to dealing with grouped data than the simple clustering of standard errors used in the section above, and is now computationally feasible given more manageable sample sizes. Specifically, the model estimates:

$$\Pr(y_i = 1) = \text{logit}^{-1}(\mathbf{X}_i\beta + \alpha_{j[i]}), \text{for } i = 1, \ldots, n \tag{2}$$

$$\alpha_j = \text{N}(U_j\gamma, \sigma_\alpha^2), \text{for } j = 1, \ldots, 403, \tag{3}$$

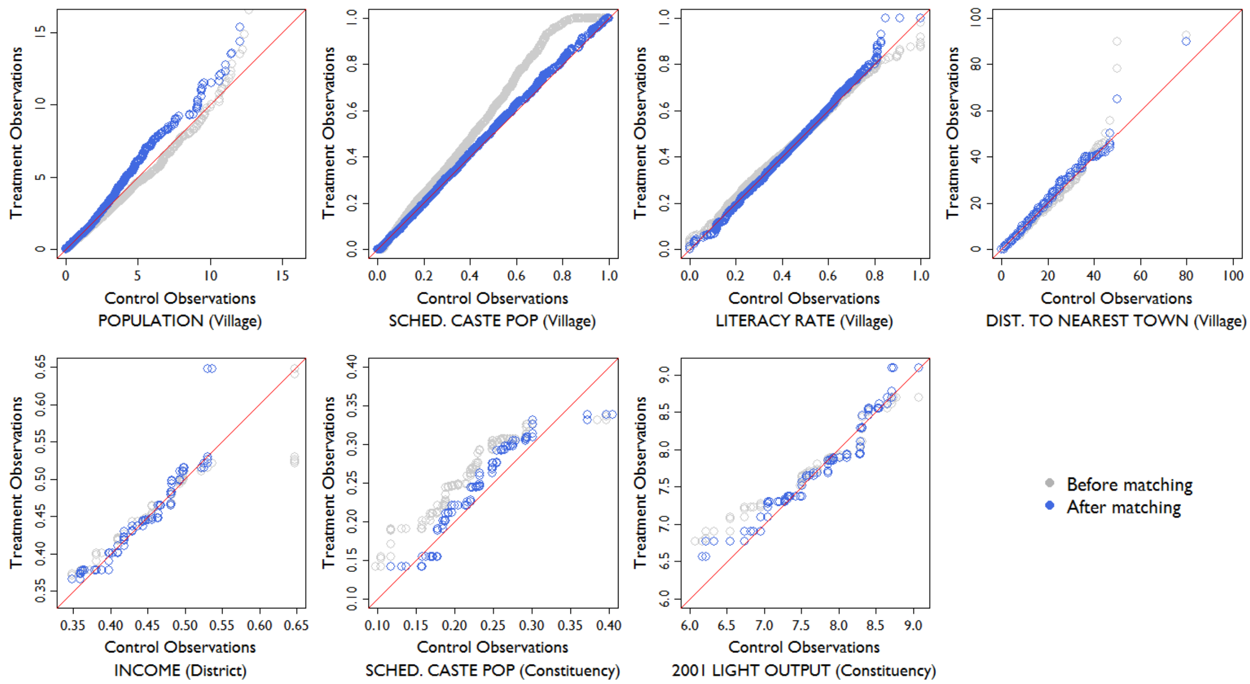
where $\mathbf{X}$ is a matrix of village-level covariates and $j[i]$ is an index indicating the constituency in which village i is located. At the constituency level, $\mathbf{U}$ is a matrix of constituency-level predictors, γ is the vector of coefficients for the predictors, and σ_α^2 is the variance of the constituency-level errors (Gelman & Hill 2007). The multilevel model estimates both equations at the same time, thus avoiding collinearity problems, while accounting for both village- and constituency-level variations in estimating the key constituency-level coefficient of BSP representation.

Table 5 presents the main results using the matched samples. The lefthand models evaluate the Dark sample, asking whether perviously unelectrified villages that switched to BSP representation were more likely to be lit than those that stayed with the BJP. The coefficient on the BSP treatment indicator is positive and statistically significant in both the reduced (model 1) and full specifications (model 2). In contrast, within the Lit sample presented on the righthand side, there is no statistically significant effect of BSP representation on whether an electrified village goes dark after the election.

The fact that BSP legislators are effective at getting villages newly electrified while being ineffective at reducing the incidence of severe power failures and blackouts may reveal both political

Figure 5: Empirical-QQ Plots of Key Covariates, Before and After Matching

Dark Sample of Unelectrified Villages in 2001



Lit Sample of Electrified Villages in 2001

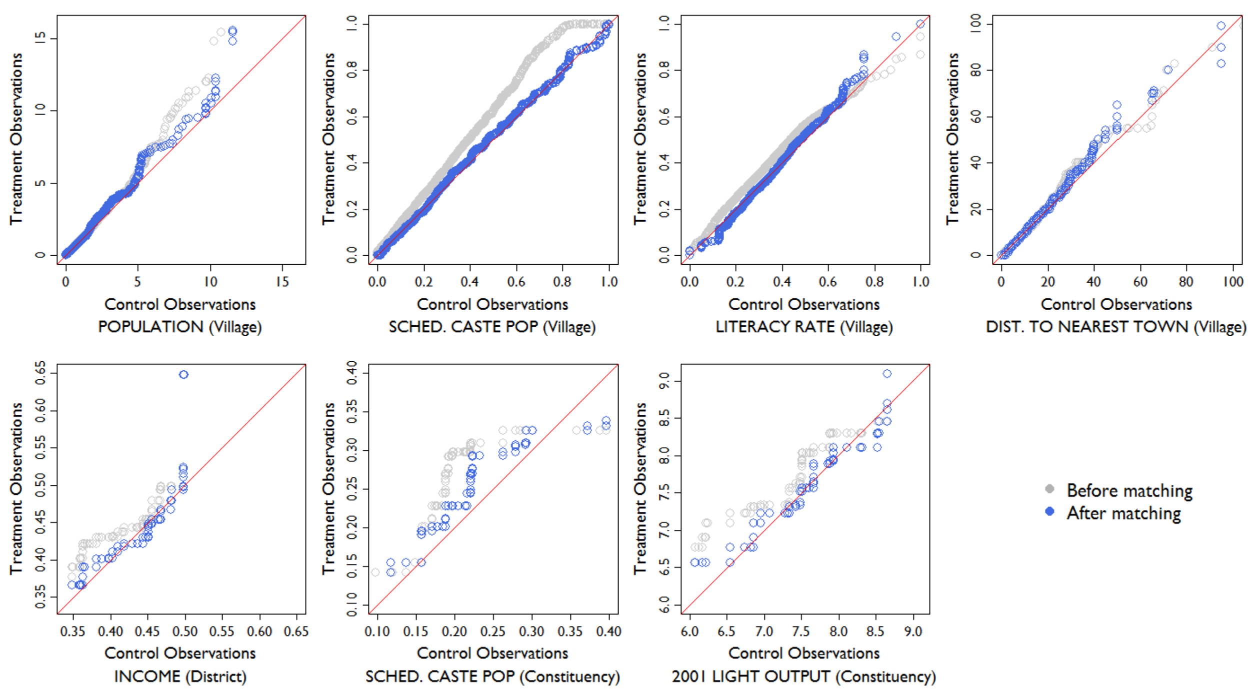


Table 5: Evaluating BSP Treatment Effects on Village Electrification
Random Effects Logistic Regressions on Matched Samples

	DARK SAMPLE (Unelectrified villages in 2001) DV: Newly Lit in 2003			LIT SAMPLE (Electrified villages in 2001) DV: Newly Dark in 2003		
	(1)	(2)	(3) BSP treatment villages only	(4)	(5)	(6) BSP treatment villages only
BSP treatment	1.6680*	1.9314*		0.2113	0.4356	
	(0.7663)	(0.7910)		(0.7377)	(0.6274)	
Scheduled Caste population share		1.3190**	12.8829*		0.5180**	-2.6445
		(0.4435)	(6.0193)		(0.1470)	(6.4719)
BSP treatment $\times$ SC pop. share		-1.7844**			-0.5868**	
		(0.5930)			(0.2101)	
Surplus of core support			-13.3258*			2.5375
(SC pop. share − BSP vote share)			(6.0032)			(6.4706)
Village-level controls						
Village population (thousands)		-0.0527	0.0817		-0.0162	-0.0227
		(0.0477)	(0.0567)		(0.0247)	(0.0322)
Literacy rate in village		2.3317**	2.5245**		-0.6747**	-0.8379**
		(0.5875)	(0.7913)		(0.2222)	(0.3175)
School in village		-0.3617*	0.0530		0.0773	0.1912*
		(0.1663)	(0.2261)		(0.0560)	(0.0825)
Medical facility in village		0.0299	-0.3357		0.0402	0.0133
		(0.1295)	(0.1905)		(0.0646)	(0.0930)
Paved approach road to village		0.5063**	0.4118*		-0.1787**	-0.2897**
		(0.1203)	(0.1766)		(0.0512)	(0.0737)
Distance to nearest town (in km)		-0.0368**	-0.0481**		0.0419**	0.0284**
		(0.0090)	(0.0133)		(0.0035)	(0.0044)
Constituency-level controls						
Income index	12.0242*	6.4064	29.3182**	7.4932*	4.0600	-0.5335
	(5.7739)	(6.1200)	(6.6172)	(3.4230)	(3.2341)	(3.2805)
2001 Nighttime light output (log)		1.0654	1.2930*		-1.9016**	-2.2810**
		(0.6189)	(0.5682)		(0.4903)	(0.6670)
Reserved constituency		-0.2551	-1.5314		0.4383	0.0491
		(0.9561)	(6.0473)		(0.8086)	(0.8459)
Scheduled Caste pop. share		-0.5918	-20.8200**		1.5721	13.7805
		(6.8396)	(6.0473)		(5.8276)	(7.3783)
Constant	-9.3191**	-15.5634**	-24.8634**	-5.7484**	10.0353**	13.6551*
	(2.4363)	(4.6062)	(4.8631)	(1.6765)	(3.6437)	(5.5121)
Observations	5358	5358	2679	14052	14052	7026
Constituencies in sample	56	56	29	85	85	37

Standard errors in parentheses.
** p-value $\leq$ .01, two-tailed test. * p-value $\leq$ .05, two-tailed test.

priorities and reflect technical constraints. In a power crisis, electricity shortages must be balanced across the state to protect the electrical grid. Massive blackouts roll across vast swaths of the state at a time and all villages in its path suffer indiscriminately. On the other hand getting a village electrified is a targeted action that requires positive steps and coordination on the part of a string of officials. Against the backdrop of massive power blackouts, the emergence of new lights is a particularly notable and visible sign of political effort towards voters. The positive BSP party coefficient suggests that new BSP legislators have indeed taken an active role in ensuring new village electrification.

Having established an overall positive effect of BSP representation, I turn now to asking what kinds of villages within BSP constituencies were most likely to garner the attention of their legislators. Specifically, I look for heterogenous effects of BSP representation across villages with different concentrations of Scheduled Caste residents by including an interaction term between BSP representation and the SC population share in each village. Scheduled Caste voters represent the strongest core support group for the BSP, and their concentration varies widely across villages, even within the same constituency. The interaction term takes advantage of the fact that the level of core support for the BSP can be estimated in an unusually precise way using Census data on SC residents in each village.

Combining the coefficients on the interaction term and the main terms reveals a surprising trend: villages in new BSP constituencies with large Scheduled Caste population shares are *less likely* to gain electrification than those with smaller SC populations. What the data reveal is that new BSP legislators seek to electrify villages with lower SC populations and thus fewer core supporters and more swing voters, even after controlling for a wide range of factors.

For BSP politicians, an even more relevant number may be how the share of core supporters relates to the percentage of votes needed to win the seat, since competitiveness can vary across constituencies. The *Surplus of core support* variable is the difference between the village SC population share and the vote share received by the BSP in the constituency in 2002.[25] Positive values identify high core support villages with a higher share of SC residents than that needed to win the seat, while negative values indicate relatively low core support villages. For example, in the constituency of Sarvankhera just west of Kanpur, the BSP candidate, Ram Swaroop Singh, won with 32% of the vote, beating the BJP incumbent Mathura Prasad. Of the 127 villages that were unlit in 2001 during

[25] In the 2002 election, successful BSP candidates won with an average vote share of 33%.

the BJP era, 11 villages were newly lit by 2003. Among the 11 newly lit villages, the villages of Gadanpur and Mohana had SC population shares of 54% and 36%, or a core support surplus of 22% and 4% respectively. The other 9 villages had an average SC population share of 20%, or an average core support deficit of -12%. Thus in Sarvankhera, most of the villages that benefited from new electrification were low core support villages.

Models 3 and 6 evaluates how the surplus of core support affects village electrification rates *within* new BSP constituencies. Since I am interested in evaluating the relative effects of a surplus or deficit of core supporters, I retain the SC population share variable in the models. The results show that while the probability of gaining new electrification is increasing as a function of SC population share, villages with a large surplus of core supporters are significantly *less* likely to gain new electrification than villages with small numbers of core supporters. When it comes to the likelihood of becoming unelectrified, the effects of SC population share and surplus core support are insignificant.

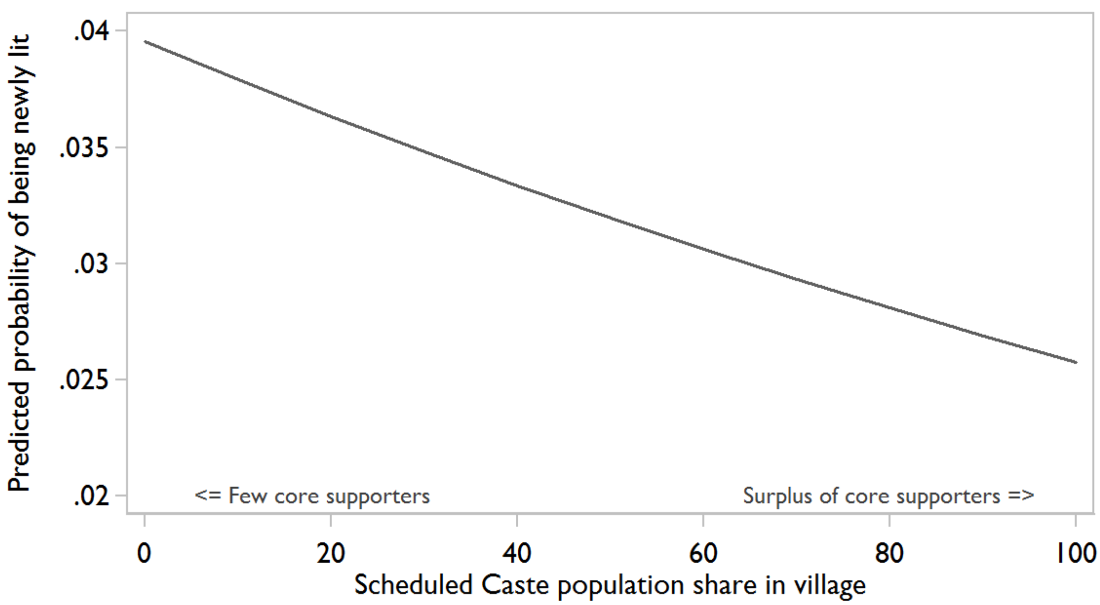
Figure 6 plots the predicted probability of a village gaining light in a BSP constituency as a function of SC population shares. The downward sloping line represents a substantively significant trend: a dark village with a 60% SC population share has a 3.1% probability of being newly lit compared to a 3.8% probability for a village with a 10% SC population share, a relative difference of 20%.

The fact that villages with fewer SC voters and core supporters were more likely to be lit under the new BSP regime is interesting given the strong pro-SC slogans and party platform of the BSP. Mayawati's Ambedkar Village program, for example, was explicitly oriented to pour development funds into the poorest Dalit villages. Yet the electrification patterns observed in 2003 suggest that within their constituencies, BSP legislators were more effective at electrifying villages with fewer Dalits, even after controlling for a wide range of other village and constituency-level factors.

This pattern plausibly reflects the consequences of UP's ethnically polarized political climate. Caste-based voting was the dynamic by which the BSP has been able to achieve electoral success. But when voters support a party based on ethnic or Caste-based affinities, politicians have few incentives to cater to the needs of their core supporters, since their votes are assured. Given that SC voters have few credible party alternatives to support, BSP legislators appear to be making calculated decisions to invest their resources in villages with fewer core supporters. The patterns also foreshadow the remarkably successful 2007 BSP electoral strategy in which it built unprecedentedly broad coalitions

Figure 6: Predicted Probability of Being Newly Lit in BSP Constituencies

[95% confidence intervals to be added]



Predicted probabilities based on Table 5, Model 3. All other variables set at means; BSP vote share set at 0.33.

of poor supporters, including across Caste lines.

The control variables behave mostly as expected. Less remote villages that are closer to a town and have a paved access road have a higher likelihood of being electrified and a lower chance of being unelectrified. Similarly, villages with higher literacy rates are more likely to be newly lit and less likely to go dark. Other village characteristics are less statistically significant, although villages with a school appear slightly less likely to receive new electrification. This could be a substitution effect in which politicians target electrification to villages that have less infrastructure, though more investigation is needed. Once village-level factors are accounted for, the average income level of the constituency is no longer a significant predictor of changes in electrification. Constituencies with higher total light output in 2001, which proxies for power grid density and quality, are less likely to have villages going dark, but does not predict new electrification projects.

7 Conclusion

This paper uses a novel set of satellite imagery of the earth at night to study variations in the provision of electrical power across Uttar Pradesh. By examining a period of substantial political change in one of India's poorest states, I show that villages have benefited from the rise of the lower Caste BSP over the last two decades. Using annual data on village electrification from 1992 to 2003, I show that the probability of being electrified is substantially and significantly higher in constituencies represented by the low Caste BSP party. Using matching techniques to evaluate similar villages that differ only on whether they switched to BSP representation in the critical 2002 elections, I also show a positive BSP treatment effect.

The timeframe observed in this paper stops short of capturing more recent developments that invite further analysis. Two developments in particular are worth noting. First, in 2005, India's central government announced an ambitious pledge to electrify all unelectrified villages in India, at a projected cost in excess of $US 12 billion. The plan, known as the *Rajiv Gandhi Grameen Vidyutikaran Yojana* (RGGVY) initiative, promised to electrify nearly 125,000 villages by 2009 and connect all households by 2012. Responsibility for implementation and management of the program would be at the state level with 90% cost subsidies provided by the center. But as 2009 began, Uttar Pradesh and many other states were far behind schedule and only 55,000 villages — less than half of the target total — had been electrified.[26]

Second, in UP's 2007 state assembly elections, Mayawati and the BSP party won a surprising majority of assembly seats, giving unprecedented power to the BSP over state policy making. Mayawati's majority victory in 2007 was secured by gaining votes among an unexpectedly wide cross-section of poor voters. According to one expert opinion, "Perhaps no electoral verdict has combined all the axes of social disadvantage in our society — caste, class, gender, region and urban-rural — as the BSP's victory."[27] With more political power than it has ever before held, observers are watching closely to see whether the BSP will be able to deliver on its promise to be the party of "*bijli, sadak, paani*." More recent satellite data state assembly elections should be available in the near future. This would allow for an illuminating extension of the analysis presented here.

[26]"Five years on, plan fails to add sparkle," *Mint*, 4 March 2009

[27]Yogendra Yadav and Sanjay Kumar, Poor man's rainbow over UP, *Indian Express*, May 17, 2007.

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Appendix

Table 6: Evaluating BSP Treatment Effects on Village Electrification
Random Effects Logistic Regressions on ***Unmatched Samples***

	Dark Sample (Unelectrified villages in 2001) DV: Newly Lit in 2003			Lit Sample (Electrified villages in 2001) DV: Newly Dark in 2003		
	(1)	(2)	(3) BSP treatment villages only	(4)	(5)	(6) BSP treatment villages only
BSP treatment	1.0236	0.9037		0.2303	0.5397	
	(0.6084)	(0.6305)		(0.6107)	(0.5283)	
Scheduled Caste population share		-0.4696	12.8829*		0.3221	-2.6445
		(0.6558)	(6.0193)		(0.1823)	(6.4719)
BSP treatment X SC pop. share		-0.0997			-0.3831	
		(0.7565)			(0.2359)	
Surplus of core support			-13.3258*			2.5375
(SC pop. share − BSP vote share)			(6.0032)			(6.4706)
Village-level controls						
Population, village (in thousands)		2.5873**	0.0817		-0.0389	-0.0227
		(0.5593)	(0.0567)		(0.0221)	(0.0322)
Literacy rate in village		0.0705	2.5245**		-0.3539	-0.8379**
		(0.1628)	(0.7913)		(0.2184)	(0.3175)
School in village		-0.2326	0.0530		0.1214*	0.1912*
		(0.1460)	(0.2261)		(0.0578)	(0.0825)
Medical facility in village		0.2097	-0.3357		-0.0369	0.0133
		(0.1306)	(0.1905)		(0.0616)	(0.0930)
Paved approach road to village		-0.0287**	0.4118*		-0.1761**	-0.2897**
		(0.0091)	(0.1766)		(0.0522)	(0.0737)
Distance to nearest town (in km)		12.8120*	-0.0481**		0.0404**	0.0284**
		(5.4762)	(0.0133)		(0.0034)	(0.0044)
Constituency-level controls						
Income index	16.6825**	0.0140	29.3182**	1.0113	-0.9103	-0.5335
	(5.2632)	(0.5251)	(6.6172)	(3.1460)	(2.9837)	(3.2805)
Nighttime light output, 2001 (log)		0.7046	1.2930*		-1.5916**	-2.2810**
		(0.4454)	(0.5682)		(0.3706)	(0.6670)
Reserved constituency		0.0527	-20.8200**		0.5535	0.0491
		(0.0477)	(6.0473)		(0.6646)	(0.8459)
Scheduled Caste pop. share		-2.5379	-20.8200**		-0.5065	13.7805
		(5.4108)	(6.0473)		(4.5377)	(7.3783)
Constant	-10.7466	-14.5531**	-24.8634**	-2.7470	10.2377**	13.6551*
	(2.2399)	(3.3334)	(4.8631)	(1.5203)	(2.6308)	(5.5121)
Observations	5902	5902	2679	13083	13083	7026
Assembly Constituencies in sample	58	58	29	89	89	37

Models 3 and 6 are identical to results in Table 5.
Standard errors in parentheses. ** p-value ≤ .01, two-tailed test. * p-value ≤ .05, two-tailed test.