



BIROn - Birkbeck Institutional Research Online

Aklin, M. and Cheng, Chao-Yo and Urpelainen, J. (2020) Inequality in policy implementation: caste and electrification in rural India. *Journal of Public Policy* 41 (2), pp. 331-359. ISSN 0143-814X.

Downloaded from: <https://eprints.bbk.ac.uk/id/eprint/47016/>

Usage Guidelines:

Please refer to usage guidelines at <https://eprints.bbk.ac.uk/policies.html>
contact lib-eprints@bbk.ac.uk.

or alternatively

Inequality in Policy Implementation: Caste and Electrification in Rural India*

Michaël Aklin
University of Pittsburgh

Chao-yo Cheng
University of California, Los Angeles

Johannes Urpelainen
Johns Hopkins SAIS

February 13, 2020

Abstract

We examine unequal outcomes in the implementation of India's national rural electrification program in Uttar Pradesh. We ask two questions: (1) to what extent did Dalits, the lowest group in India's caste hierarchy, receive less attention when the state electrified rural communities? (2) Was BSP, the state's Dalit party, able to reduce this inequality? Using data from a hundred thousand villages, we provide robust evidence for unequal outcomes. Villages inhabited solely by Dalits were 20 percentage points less likely to be covered by the program than villages without any Dalits. Moreover, a regression discontinuity analysis shows that the electoral success of BSP failed to reduce such differences. These results highlight the magnitude and persistence of caste inequality in the implementation of democratic public policy, despite political representation.

*We thank the Council on Environment, Energy and Water for their contribution to this research project and MORSEL India for excellent data collection. The survey for this project was funded by the Shakti Sustainable Energy Foundation and ClimateWorks Foundation. We thank Oliver Vanden Eynde and Jacob Shapiro for sharing data on rural electrification. We thank seminar audiences at Strathclyde University, the Indian Institute of Dalit Studies, and the National University of Educational Planning and Administration for helpful comments. We are also grateful to Tariq Thachil, Adam Ziegfeld, and Simon Chauchard for comments. A replication archive is available at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/KBTHZH>.

1 Introduction

From economics (Becker, 1957) to social psychology (Tajfel et al., 1971) and political science (Bullard, 1990), researchers have documented inequalities between majority and minority groups. While much is known about discrimination by individuals and private firms, unequal outcomes in the implementation of public policy are less understood. In particular, most studies focus on bias against marginalized groups within social or market interactions (e.g., Oliver and Wong, 2003; Bertrand and Mullainathan, 2004; Banerjee et al., 2009; Kaas and Manger, 2012; Guryan and Charles, 2013). Although several scholars explore governments' biases in favor of their own ethnic group (e.g., Franck and Rainer, 2012; Posner and Kramon, 2013), they usually focus on cross-group disparities in broad development *outcomes*. Recent studies explore differential responsiveness of bureaucrats to citizen requests from different racial and ethnic groups (e.g., Distelhorst and Hou, 2014; White, Nathan, and Faller, 2015; McClendon, 2016), instead of large-scale public policies.

In response to inequality, ethnic parties around the world are advocating for the rights of their perceived co-ethnics (Chandra, 2007). The notion of social “empowerment” plays a central role in contemporary debates about inclusive growth (Drèze and Sen, 2002; Alsop, Bertelsen, and Holland, 2006). However, it remains unclear whether this kind of political mobilization can reduce inequality in public policy implementation.

Here we explore the case of India’s “untouchables,” now known as Dalits, who were at the bottom of the hierarchy in traditional Indian society (Bayly, 2001). In today’s rural India, caste inequality remains prevalent despite affirmative action and political representation (Banerjee, Iyer, and Somanathan, 2005; Thorat and Newman, 2012). For example, the 2011-2012 India Human Development Survey finds that 41% of non-Dalit rural households across the country continue to practice “untouchability,” while 38% of Dalit rural households report that they have experienced caste discrimination.¹ The Dalit population of India, estimated at over two hundred million individuals (Government of India, 2013: 25), thus suffers from poor outcomes and extensive bias.

We examine the targeting of rural electrification efforts in India’s most populous state, Uttar Pradesh (UP). Access to electricity is one of the most basic and important public goods, given

¹See <http://ihds.info> (accessed September 22, 2016) for more information about the IHDS survey.

its importance for health, economic opportunities, and overall life comfort (Khandker et al., 2009; Khandker, Barnes, and Samad, 2013). With a total population of two hundred million and a low rural electrification rate of 24% in the 2011 Census of India, UP is an ideal setting for examining the distributional logic of rural electrification. In areas characterized by such high levels of energy poverty, electrification is in high demand across all social groups (Aklin, Cheng, Urpelainen, Ganesan, and Jain, 2016). Thus, differences in tastes are not driving disparities across groups.

India's national rural electrification program, the Rajiv Gandhi Rural Electrification Scheme (RGGVY), targets villages for rural electrification and thus provides an excellent opportunity to detect inequality in implementation at the community level. An exclusive responsibility of the state, rural electrification in India allows us to directly link policy implementation to the caste structure of a hundred thousand villages. Focusing on policy instead of social outcomes allows us to establish a closer link between officials' behavior and inequality. Moreover, given that every fifth person living in the state is from the lower castes, UP is an excellent locality to explore caste biases in public policy implication.

Drawing from the 2001 and 2011 census data and the information of RGGVY implementation at the village level, we study patterns of rural electrification as a function of demographic and socio-economic characteristics. We estimate how the proportion of the scheduled caste (SC) population – the legislative category for Dalits – affects the probability of RGGVY implementation in a village. A comprehensive analysis reveals significant evidence of inequality. Consistent across a wide range of different model specifications, we find that an increase in the share of SC population in a village of one percentage point is associated with a reduction in the likelihood of RGGVY implementation of 0.15-0.20 percentage points. The estimated effects of SC population size, in turn, explain why villages populated by Dalits have such low rural electrification rates in the 2011 census. Electric lighting is only used by 17% of the population in villages that are populated by Dalits. While our method cannot detect *intentional discrimination*, it offers a systematic overview of *unequal, biased policy implementation* in a large-scale public program of great importance for rural development.

Next, we examine whether political mobilization curbs inequality. Both in India and elsewhere, the victims of bias have mobilized politically to fight against bias and for justice and social inclusion.

In UP, the Dalits have formed their own party, the Bahujan Samaj Party (BSP) in the 1980s (Bose, 2013; Pai, 2014). After the 2002 and 2007 state elections, the BSP formed the state (coalition) government in UP. Following the literature on political alignment in distributive politics (Dynes and Huber, 2015; Asher and Novosad, 2017), we thus have the opportunity to study whether BSP's electoral victories reduce the level of inequality in RGGVY implementation.

Exploiting India's plurality electoral system and intense competition with narrow margins of victory, we conduct a regression discontinuity analysis of the effects of BSP candidates winning close elections on RGGVY implementation across the villages. Because of wide variation in the SC population share across villages within any of UP's constituencies, we can see whether a BSP Member of Legislative Assembly (MLA) can guard his or her primary constituency – the Dalits – against weak policy implementation. The results suggest that the BSP's electoral success has failed to protect Dalits against bias. Regardless of the share of SC population in a village, BSP electoral victories do not cause a reduction in RGGVY inequality. As a possible explanation, we show that Dalit candidates are a tiny minority outside constituencies specifically reserved for them under Indian election law. Using original data on MLA caste backgrounds, we show that outside electoral quotas for Dalits, even the BSP prefers to use non-Dalit candidates. Thus, the BSP's electoral success does not actually result in descriptive representation for the Dalits.

These findings offer contributions to research on ethnic and racial inequality. While discrimination against marginalized groups is a well-known phenomenon, our study sharpens the picture in several ways. First, we document inequality in a major development initiative from the world's largest democracy. India's rural electrification program is the largest in the world and could improve the lives of hundreds of millions, but our results suggests that these improvements are less available for weak minorities. While earlier studies have shown evidence of ethnic discrimination by legislators and bureaucrats, ours is the first to examine inequality in public policy implementation on a large scale at the community level. Furthermore, we also find that policy discrimination on its own is substantially large. Our robustness checks also rule out alternative explanations, such as Dalits lagging behind in electrification due to poverty or a lack of capacity for collective action.

Equally important is our finding on the ineffectiveness of political mobilization. While we

must exercise due caution in generalizing our null result, it is notable that a major political party with the mandate to protect the rights of a particular minority group is unable to do so even in the context of a government development initiative. This result contrasts with theories that emphasize the importance of ethnic representation for material outcomes, such as Chandra's (2007) "head counts" approach to ethnicity in electoral politics. The result also suggests that although descriptive representation of Dalits may reduce individuals' "discriminatory intentions" at the local level (Chauchard, 2014; Dunning and Nilekani, 2013) and electoral quotas increase pro-Dalit public spending (Pande, 2003), the electoral success of Dalit-oriented parties may produce disappointing results unless they actually unleash a wave of descriptive representation in the state legislatures. In closely related research, Min (2015) reports a positive relation between BSP representation and the supply of electricity to villages in UP at election time. In contrast, our focus is on inequality over policy implementation. We show that the benefits of BSP's electoral success in the context of India's most important rural electrification program have been limited. Our result raises doubts about the BSP's willingness or ability to promote Dalit interests in rural development.

2 Inequality in Public Policy Implementation

Studies have provided robust evidence for discrimination, bias, and inequality in human society. Tajfel et al. (1971) offer experimental evidence of "in-group bias," as individuals treat their peers from the same group favorably. Likewise, governments may favor individuals that belong to their group, whether it is for opportunistic or psychological reasons (e.g., Franck and Rainer, 2012; Posner and Kramon, 2013; McClendon, 2016). In-group bias, however, is not the only form of discrimination. The flip side of the coin is *social exclusion* (Thorat and Newman, 2007), which refers to individuals' tendency to marginalize a particular racial and ethnic group. Resentment may be driven by "taste" or by "statistical" cues (Becker, 1957; Arrow, 1998). Those responsible for carrying out and sustaining discrimination in the society do not necessarily belong to a well-defined and cohesive social group but involve multiple groups.

The literature on racial politics in the United States has contributed by showing the predicaments of racial minorities across a wide range of transactions in the private sector, such as car dealings (Ayres and Siegelman, 1995) and housing sales (Yinger, 1997). Previous studies have also

shown varieties of bias against particular minority groups through wage differentials and preferential hiring in the labor market (e.g., Lovell, 1993; Bertrand and Mullainathan, 2004; Kaas and Manger, 2012; Guryan and Charles, 2013).

Scholars of institutionalized racism focus on discrimination in public life. Researchers have documented how discrimination shapes U.S. court verdicts and law enforcement (e.g., Alesina and Ferrara, 2011; Chen, 2013; Sen, 2015). Recent experimental work has also demonstrated that elected representatives and public officials often behave differently based on the race of their constituencies. Butler and Broockman (2011) find that state legislators, regardless of their party affiliations, tend to be less responsive to African American constituencies. Likewise, White, Nathan, and Faller (2015) find that local election administrators in the US are less likely to reply to requests from putative Latino names and are more likely to provide poor information about voter ID laws. Einstein and Glick (2016) uncover evidence for the lack of respectful treatment toward Hispanics by government officials.

The studies mentioned above identified patterns of social exclusion in individual citizen-bureaucrat interactions. Our aim and contribution is different. We examine whether and how a large-scale infrastructure program is biased against a low-status minority, the Dalits, in India (Deshpande, 2000). Access to public goods varies enormously within the country (Spears and Lamba, 2013). Existing studies have mostly focused on examining the pattern and practice of social exclusion based on interpersonal communication, including the interactions between politicians, government officials, and minority citizens. For instance, in the Indian context, Bros and Couttenier (2010) show how private violence against Dalits is related to access to water. Few existing studies seek to uncover inequality in large-scale public programs, despite the fact that studies have established inequality in access.

3 Background and Context

We now describe the context of our assessment: caste inequality in a national program of rural electrification in UP.

3.1 Rural Electrification in India and RGGVY

When India gained independence in 1947, electrification was limited to a small number of urban areas (Kale, 2014). Over time, the need to electrify pumpsets to extract groundwater for the high-yield plant varieties introduced under the agricultural green revolution enabled rural electrification (Smith and Urpelainen, 2016). And yet, according to the 2001 census of India, only 44% of rural households used electricity as their primary source of lighting.

In India, the governance of the electricity sector is a “concurrent” subject, with both the central and state governments having policy authority. While electricity distribution companies are controlled by state governments, except under privatization in Odisha and the capital city of Delhi, the central government is also authorized to initiate schemes to promote rural electrification. This multi-level governance structure is essential to understanding how the RGGVY is implemented.

Launched in April 2005 by Dr. Manmohan Singh’s (Indian National Congress) central government, the goal of the RGGVY was to increase the rate of rural electrification across India. At the initiation of the RGGVY, the government announced that the “scheme has been launched to fulfill the commitment of the National Common Minimum Programme (NCMP) of completing the household electrification in next 5 years and modernizing the rural electricity infrastructure.”²

In the RGGVY, the central government provides a 90% capital subsidy for the electrification of villages; the remainder is provided by the national Rural Electrification Corporation as a soft loan. While the RGGVY is a village electrification scheme, households living below the official poverty line are guaranteed free electric connections. State governments can apply for the funds, provided they agree to implement the scheme according to the guidelines set by the central government. Until 2007, only habitations (sub-village units) with more than 300 people according to the 2001 Census were eligible; at that time, the population floor was decreased to 100 (Burlig and Preonas, 2016). While all villages qualify for the electrification subsidy regardless of socio-economic status, RGGVY also gave households below the national poverty line a free household connection.

The actual *selection* of villages and habitations for RGGVY implementation is the responsibility of district-level administrative and technical officials, such as the Chair of District Council (*Zilla*

²See http://powermin.nic.in/upload/pdf/Rajiv_gandhi.pdf (accessed May 18, 2016).

Parishad), District Magistrate (or Collector), and Electricity Engineers. They work closely with their respective MLAs and Block Development Officers. In India, district-level officials enjoy a lot of discretion in implementing poverty alleviation programs introduced by the central government in Delhi. Focusing on the Employment Assurance Scheme (EAS), Corbridge et al. (2005) find that district-level officials often revise the details of implementation and collaborate with MLAs to screen eligible recipients for political reasons.

As a result, village selection under RGGVY similarly provides politicians ample opportunity to target the policy according to their own preferences.³ The formal rules specifically encourage RGGVY implementation to consider the special needs of the Dalits: “[b]asic infrastructure such as distribution transformer and distribution lines is provided in the inhabited locality as well as the Dalit basti/hamlet where it exists” (Ministry of Power, 2013: 3).

The RGGVY has achieved its goal of rapid rural electrification (Aklin, Cheng, Urpelainen, Ganesan, and Jain, 2016; Burlig and Preonas, 2016). By the end of the financial year 2012, the program had reached a total of 104,496 un-electrified villages and another 248,553 previously electrified villages for intensification – that is, more than one-half of all villages in India. Within villages, 19.5 million households living below the official poverty line were electrified. As Burlig and Preonas (2016) show, the RGGVY has not had large economic effects in targeted villages, but it has significantly increased electricity access.

In UP, a May 2012 assessment of program implementation shows that 27,770 non-electrified villages were electrified and 2,982 electrified villages saw improvements through intensive electrification by the end of 2011 across 63 districts. Compared to a goal of 32,118 villages set by the state government, the achievement rate was thus 96%. At the same time, the number is very low relative to the total number of villages in the state: according to the 2011 Census of India, UP had 106,773 villages. By our analysis, 96,557 of these villages were inhabited (Indian census also includes abandoned villages in the total number). Thus, only about 31% of all UP villages saw RGGVY implementation by the time of the assessment even though almost all villages in the state perform poorly with regard to electrification: the average household electrification rate in a typical

³For a detailed description of RGGVY, see Ministry of Power (2013).

UP village in the census was only 23%.⁴

3.2 Caste Inequality in India

Scholars have documented persistent patterns of social bias in India against both religious minorities, such as Muslims and Christians (Hasan, 2009), and against Dalits (Scheduled Castes) (Bayly, 2001; Louis, 2003; Kapur et al., 2010; Thorat and Newman, 2012). In the case of *Dalit* discrimination, some members of the upper caste groups consider their low-caste counterparts socially inferior. As Thorat and Lee (2005: 4198) note, for example, shopkeepers belonging to upper castes may refuse to trade with Dalit customers “until they have hung cloth screens in a place to ‘protect’ themselves from the polluting presence of the ‘untouchables’.” Experimental audit studies from Indian labor markets show that Dalits often face obstacles in finding employment (Banerjee et al., 2009). These results highlight the fact that caste bias remains common in India, as higher castes often hold negative attitudes toward the lower castes and refuse to engage in social or economic exchange with them. Tolerance of discrimination remains widespread across large segments of the population (e.g., Shah et al., 2006; Kapur et al., 2010; Ramaiah, 2011).

Caste inequality can take at least three forms (Shah et al., 2006). First, physical exclusion, the most common form of untouchability, involves members of upper castes refuse and avoid contacts with those from the Scheduled Castes through residential segregation and denials of commercial exchanges and services, food sharing and water distribution (e.g., Bros and Couttenier, 2010), and access to public facilities. Next, untouchability also involves public humiliation, as dominant castes restrict the Dalits from using vehicles, smoking, or even holding their wedding processions. Finally, upper castes have also economically exploited the Dalits by blocking the Dalits from certain employment opportunities (e.g., Siddique, 2011) and underpaying them. Here we examine these patterns of caste inequality in the case of the RGGVY, a large-scale public policy financed by the central government and implemented by the state governments.

Despite the government’s various legal and policy efforts to eradicate caste bias, untouchability remains widespread in India, especially in the rural areas. Even worse, recent years have seen the

⁴The numbers remain similar if we limit our sample to villages with more than 300 inhabitants (RGGVY’s earlier threshold): RGGVY was implemented in about 30% of these villages.

emergence of collective, organized violence targeting the Scheduled Castes who seek to assert their rights (Chauchard, 2017). In several cases, these “atrocities” took place because local elites aim to maintain their dominance and privilege in the face of increasing economic competition from the Dalits (e.g., Sharma, 2015).

Although caste inequality in the society and the private sector has been carefully documented, including with experimental methods that can identify causal effects, it remains unclear whether a bias remains in public policy itself. Thorat and Lee (2005: 4198) use survey data from 531 villages in five states to show that “patterns of exclusion and caste discrimination ... afflict, if not overwhelm, the government India’s mid-day meal scheme.” However, it remains unclear whether such patterns reflect policy implementation by the government or, alternatively, the social behavior of the people who use or prepare mid-day meals in Indian schools.

Solutions to the problem of caste inequality have proven elusive. In India, the most important national policies against caste bias are educational, employment, and representation “reservations” (Jaffrelot, 2006; Bhavnani, 2017), which guarantee both the scheduled castes and scheduled tribes (*adivasis*) a certain percentage of admissions to public institutions of higher learning, government jobs, and seats in different political bodies from village councils (*gram panchayats*) to state legislative assemblies and the national parliament. However, it appears that these reservations have not effected a social revolution: the evidence on the socio-economic effects of reservations suggests that they are weak (Jensenius, 2015), though they have contributed to policy changes and political mobilization (Pande, 2003; Jaffrelot, 2006).

3.3 Caste Inequality in Rural Electrification

Rural electrification can contribute to caste inequality in UP through several channels. Because the RGGVY program design allows state governments, district-level officials, and MLAs to decide on the targeting of RGGVY implementation at the village level, the national program has a lot of scope for inequality at the implementation stage despite formal rules that base implementation on need. Therefore, examining RGGVY offers an opportunity to detect bias in public policy implementation. In turn, bias in implementation feeds inequality when it is done in way that further weakens groups (such as SCs) that are already marginalized.

The goal of the RGGVY was to electrify as many villages as possible, and villages themselves did not have to do anything to request RGGVY implementation, and in fact lacked lobbying power to make demands (Prayas Energy Group, 2011: 27). As per the 2006 National Rural Electrification Policy of India (Ministry of Power, 2006), village heads (*pradhans*) and councils (*gram panchayats*) only had an advisory and supervisory role in RGGVY implementation. Field research conducted by Greenpeace, an environmental non-governmental group, finds that fewer than 10% of villagers in Madhubani district, Bihar, were aware of RGGVY even though their village was electrified under the scheme (Greenpeace, n.d.). Indeed, a large-scale survey of six North Indian states reveals that fewer than 50% of village heads had heard of RGGVY in 2014, after a decade of implementation (Aklin, Cheng, Ganesan, Jain, Urpelainen, and Council on Energy, Environment and Water, 2016). This basic lack of awareness suggests limited interest or ability in participating in the policy formulation process, which is not surprising given the limited authority of local government in this area.

This feature of the RGGVY is useful for us, as it ensures we cannot empirically conflate bias against lower castes with less vocal demands or less effective collective action by the scheduled castes. Given that the RGGVY is a top-down program that does not condition eligibility on active demands by villages, any bias against scheduled castes can be attributed to bias by government officials. Moreover, this feature of the RGGVY also ensures that a bias against scheduled castes in RGGVY implementation cannot be attributed to logrolling: given the RGGVY rules, communities cannot expect to gain access to other public services by forgoing electrification. The RGGVY is not part of a menu of options for villages, but rather a standalone program.

The first mechanism of bias in policy implementation is the choice of villages. According to RGGVY rules, states are allowed to choose the targeting of districts. With the average district in UP having about three million people, however, this administrative unit is too large for biased implementation: every district in UP has large numbers of both Dalit and non-Dalit communities. There is little scope for inequality in the selection of districts.

Within districts, however, local officials play a key role. The RGGVY rules state that the selection of villages remains in the hands of “the respective States/DISCOMs [electricity distribution companies] based on field survey while preparing Detailed Project Reports” (Ministry of Power,

2013: 7). Because the distribution companies in UP are state-owned, they create ample opportunities for political and bureaucratic control (e.g., Wade, 1985; Iyer and Mani, 2012). MLAs, who compete for office in constituencies that are smaller than districts, have both formal authority over the selection of local officials, such as the powerful Block Development Officers, and informal power through their popular support and networks of connections. A comprehensive assessment of the RGGVY itself in UP notes that (i) the local district-level planning leaves a lot to be desired and that (ii) state-level officials lack the capacity to properly assess the resulting plans (IRADe, 2013: 54-55), suggesting ample scope for biased implementation by local politicians. We argue, therefore, that RGGVY's inequality potential is found at the district and electoral constituency level. Due to their political power, connections, and ability to shape the careers of bureaucrats, MLAs can influence village selection for the RGGVY within their own electoral constituency.

Indeed, Section 6 of the Rural Electrification Policy of 2006 further mandates the formation of a district committee for rural electrification, with *inter alia* elected representatives from the district as members (Ministry of Power, 2006). Specifically the committees are chaired by the district panchayat's chair, the district planning committee's chair, or the district collector. Other members include district-level government agencies, consumer associations, and "other important stakeholders." This setup gives the committee chair, who must be an elected official or a high-level bureaucrat, ample scope to select his or her preferred members, as there are no specific rules to ensure broad representation. Moreover, since elections in India hold only every five years, the elected chairpersons have a long period of time to direct rural electrification to their preferred direction.

The role of the committees is to "to coordinate and review the extension of electrification in each district, to review the quality of power supply and consumer satisfaction and to promote energy efficiency and its conservation" (Ministry of Power, 2009: 35). By participating in this committee and influencing its work, the MLA has potential for shaping the allocation of electrification works across villages. As politicians and bureaucrats work together to select villages for RGGVY implementation, they can use census lists and other data sources to identify villages for preferential implementation at the expense of others. By using this information, the local administration can

thus channel RGGVY resources to the electrification of non-Dalit communities – if it so prefers.⁵

The logic of local inequality in village selection is also facilitated by the role of Members of State Assembly (MLAs) as “fixers” in their electoral constituencies (Chopra, 1996; Jensenius, 2015). In India, the typical MLA actually spends very little time in the state capital in legislative debates, and instead mostly focuses on serving the people in his or her constituency. Thus, the MLAs have a strong local presence and can influence village selection. Most MLAs spend their time in their own constituencies and thus have easy access to the district-level officials who are selecting villages for electrification.

3.4 Political Mobilization against Caste Inequality

Frustrated with the low pace of change, the Dalit population has mobilized politically against caste inequality (Mendelsohn and Vicziany, 1998; Duncan, 1999; Jaffrelot, 2003; Jaoul, 2006; Jeffrey, Jeffery, and Jeffery, 2008; Singh, 2017). Political parties are central players in Indian politics. They deliver goods for both the general public and particular interests (Chhibber and Nooruddin, 2004; Dunning and Nilekani, 2013; Kruks-Wisner, 2018). And they tend to respond to their core supporters’ demands, which makes representation crucial to obtain favorable public policies. This is particularly true for parties that are closely associated to a particular ethnic or social group (Chandra, 2007). Inequality-reducing policies, in turn, necessitate strong electoral mobilization.

Political activists such as Kanshiram and Mayawati have created their own political party, the BSP, and achieved electoral success in UP (Duncan, 1999). While the developmental achievements of the BSP remain unclear, scholarship shows that it has empowered the Dalit population to become politically active and vocal (Duncan, 1999). Describing the experience of one Dalit village with Mayawati’s program of constructing statues of Dr. Ambedkar, Jaoul (2006: 198) notes that “[t]o these villagers, installing a statue was a daring act that cashed in on the new power equation. It

⁵We make two observations here. First, while it is possible that SC-heavy areas have less competent bureaucrats than other areas, a skill-centered argument would not explain a bias against SC-populated villages. Differences in bureaucrats’ skill levels would lead to low levels of overall electrification. Our analysis includes district fixed effects and only focuses on differential village electrification likelihoods within each district. The fixed effects at the district level ensure that we leverage within-district variation in SC presence and therefore hold the quality of bureaucrats within a district constant. Second, one question is whether discrimination happens because it is widely accepted or because a few key decision-makers can impose it. We do not have data to distinguish between these two hypotheses, but we note that tolerance for discrimination against Dalits is widespread (e.g., Shah et al., 2006; Kapur et al., 2010; Dhar, Jain, and Jayachandran, 2018), which implies that discrimination could have a large basis.

gave shape to their new status, enacting a political change that would otherwise remain beyond the realm of local reality.” On the other hand, Mehrotra (2006: 4261) notes that “[s]ymbolic acts of defiance of the established ‘manuvadi’ order have indeed been dominant in UP, without much tangible benefits for the poor and the oppressed to show for it.”

The ideology and strategy of the BSP shed light on why and how the party’s politicians might be able to reduce inequality: “Although the BSP believes in total transformation i.e. destruction rather than reform of the Hindu social and political order, this revolution is to take place not through social upheaval, but the ballot box ... the first past the post system makes it possible for [Dalits] to come to power, and thereby seize power from within” (Pai, 2001: 62). Where the BSP wins an electoral seat, the local MLA can act to reduce inequality in several ways.

First, as noted above, the selection of villages within districts is a local process. In his or her own electoral constituency, a BSP MLA can exercise an influence on the selection of villages through contacts with the district committees that officially select villages. The MLA can also influence the selection of households within gram panchayats – India’s rural local governments, often comprising several villages – and thus ensuring that villages/habitations with Dalits are adequately covered. Finally, the MLA can also monitor the rural electrification process and report perceived bias to the state government.

A BSP MLA can also support rural electrification through complementary programs. One of the BSP’s key programs for Dalit empowerment has been the Ambedkar Villages Program (AVP), which channels state development funds into villages with a high percentage of Dalit population (Pai, 2004: 1145-1146). A BSP MLA can use AVP resources to support rural electrification and thus ensure that RGGVY implementation in Dalit villages succeeds.

Against these predictions, there are also reasons to be skeptical about the effect of electing particular MLAs. Corrupt, inexperienced, isolated, or ineffective MLAs will hardly be able to counterbalance the effects of discrimination. These forces could neutralize the benign effect of representation.

During our study period, the UP state government was at times led by BSP. The BSP’s leading politician, Mayawati, had intermittently served as the state chief minister in the 1990s and then

again from May 2002 to August 2003, after which BSP lost power because its coalition partner, the national Bharatiya Janata Party (BJP), withdrew. In 2007, BSP won an absolute majority in the state elections with a new electoral strategy that invited non-Dalits to support the BSP.

The BSP's attempt to form coalitions with other parties raises questions about the party's commitment to lower-caste empowerment. As Pai (2001: 63) explains, however, "[t]he BSP has tried to justify its alliances with upper caste parties since the mid-1990s, as not constituting a shift from its path of Dalit justice and upliftment but as short-term strategic alliances ... capturing political power by any means is both necessary and justified in the case of a Dalit party in UP as without it social transformation is impossible." Indeed, in the 2009 general election of India, the only caste group in UP that voted for BSP in the majority were the Scheduled Caste – both the *jatav* caste, which has historically been the key BSP constituency since its establishment, and other subcastes in the Scheduled Caste (Pai, 2014: 157). Despite the BSP's alliances with non-Dalit political forces, the core voters of the party during our study period were the scheduled castes – all other social groups in UP favored other political parties.

In sum, we expect policy discrimination that may or may not be mitigated by political mobilization. Before turning to the analysis, we highlight some of the scope conditions for our argument. Our theoretical framework applies to situations in which (a) group antipathy is widespread, (b) one group is politically weaker than others, (c) there are few mechanisms available to the disadvantaged group to correct uneven policy implementation (e.g. easy access to courts or media). The effect of political mobilization itself is contingent on the efficacy of parliamentary action, the willingness of politicians to monitor and exert pressure if they disagree with policy implementation. We believe that this model can be adapted to study other policy areas.

4 Caste Inequality in the RGGVY: Research Design

To assess the magnitude of caste inequality in public policy and the effectiveness of political mobilization, we focus on the implementation of the RGGVY in UP. The unit of analysis is a census village ($N = 96,557$). For each village, the 2011 Census of India provides information about the percentage of schedule castes (SC) in the population. Caste inequality can be identified if the SC

percentage is strongly and negatively associated with the probability of rural electrification.⁶

Let i denote a village within an electoral constituency j . To measure caste inequality, we estimate the following equation:

$$Y_{ij} = \alpha + \beta SC_{ij} + \mathbf{X}'_{ij}\gamma + \epsilon_{ij} \quad (1)$$

where Y_{ij} is a dependent variable (household electrification rate or RGGVY program implementation status), α is a constant, SC is the percentage of the total village population that belongs to the SC category, \mathbf{X} is a vector of control variables, and ϵ is the error term. In some models, we replace the constant with electoral constituency ($N = 402$) fixed effects to maintain a sharp focus on local variation across villages within the same electoral unit. Standard errors are clustered by constituency throughout. The coefficient β should be negative if caste inequality is a reality. The models are estimated with least square, though our results regarding RGGVY implementation remain stable using a logit model (Table A36).

4.1 Dependent Variable: RGGVY Implementation

The primary dependent variable is a binary indicator for RGGVY implementation in a village. The Rural Electrification Corporation of India monitors the implementation of the RGGVY, and we use their master database as of October 2014.⁷ The database is a list of villages that have been electrified under the RGGVY. While the database does not contain comprehensive or reliable data for the exact timing of village electrification, it provides us with a cross-section of RGGVY implementation three years after the 2011 Census of India. For every village in UP, we thus know whether RGGVY was implemented in it within approximately a decade of the initiation of the program, between April 2005 and October 2014.

⁶For this study, we consider scheduled tribes similar to scheduled castes. In practice, this distinction is trivial for UP, as the scheduled tribe population is tiny. In the average village in our sample, the percentage of scheduled tribes is only 0.7%, while the percentage of scheduled castes is 23.9%. This being said, we replicate our results separately for SCs and STs in Table A32 and A33, and find no substantial differences with our main results. Other groups at risk include Muslims. Unfortunately, we lack data to estimate the magnitude of bias against them in the context of RGGVY.

⁷Given that the May 2014 election brought Prime Minister Narendra Modi's Bharatiya Janata Party (BJP) into power, our database reflects electrification under the Indian National Congress. We do not expect significant measurement error; notice, however, that data manipulation would probably entail over-reporting RGGVY implementation in Dalit communities, which would bias the estimates against us.

To quantify the consequences of caste inequality, we also exploit village-level data on the percentage of households with grid electricity access. We thus repeat our main analysis but replace the RGGVY implementation indicator with the share of electrified households. We expect this share to be lower when the percentage of SC people is high at the village level.⁸

Note that access to the grid does not mean that households benefit from reliable electricity. Several studies have highlighted problems related to low hours of electricity actually available (e.g., Aklin, Cheng, Urpelainen, Ganesan, and Jain, 2016). As a result, access to the grid does not necessarily mean that households benefit from abundant electricity. This being said, we believe that modeling connections (rather than, say, hours of electricity) makes sense given our research interest. Electricity supply (i.e. hours) mostly varies across districts and sub-districts, as opposed to villages, because officials have no direct control over whether any particular village under a certain feeder receives electricity or not. Connections to the grid, on the other hand, is more immediately controllable by officials. In fact, analyzing hours of electricity offers us the opportunity to run a placebo test: we would not expect the share of SC to affect supply for the reasons we stated. And indeed, this is what we find (Table A29).⁹

4.2 Explanatory Variable: Scheduled Caste Population

The primary explanatory variable is based on the scheduled caste population of the village. The 2011 Census of India provides both the total population and the SC population of every village in UP, and we can thus compute the percentage of SC population in the village. The results remain very similar with Census data from 2001 (Table A34). Figure A3 demonstrates the considerable variation across villages in SC population. The average SC percentage in our dataset is 24.6%.

⁸Table A37 reports the estimates using nighttime lighting data as the outcome variable. The estimates are less precisely measured, which is consistent with nighttime data being more weakly correlated with household electrification data for small geographical units such as villages. This is because villages that are poorly connected to the grid also suffer from intermittent power that renders nighttime satellite data less reliable (Dugoua, Kennedy, and Urpelainen, 2018).

⁹As another specification test, we run our main models using the presence of pucca roads as the dependent variable. While there exists a program (PMGSY) to promote road construction, its design mitigates the risk of discrimination. In fact, the Government of India and the World Bank, which co-funds the program, require that vulnerable populations should receive a fair share of the program. SC are singled out as needing to be included in discussions over the “design, implementation and monitoring” of PMGSY. See #4 and #5 in Government of India, “Rural Roads Project II – Additional Financing: Vulnerability Framework” <http://documents.worldbank.org/curated/en/601681525178685938/pdf/PMGSY-AF-Vulnerability-Framework-April-2018.pdf> (accessed on December 1, 2019). And indeed, we find that the presence of SC increases the likelihood of having a pucca road.

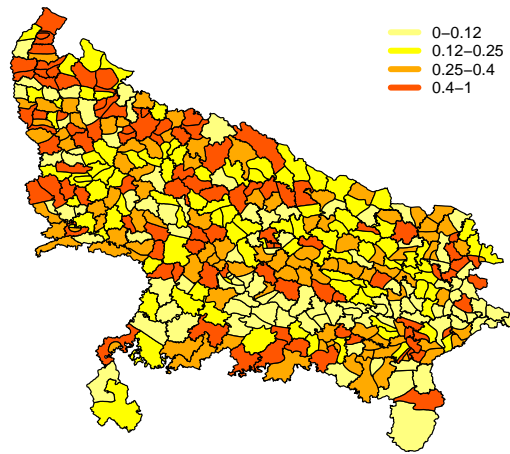
In Figure 1, we show the geographic distribution of RGGVY implementation (share of villages electrified under RGGVY) and SC share (0-1 scale) across UP electoral constituencies. In the empirical analysis, we use constituency fixed effects to ensure that geography does not bias our estimates. In Table A35, we show that the results remain qualitatively the same when allowing the share of SC to be quadratic.

4.3 Control Variables and Split Samples

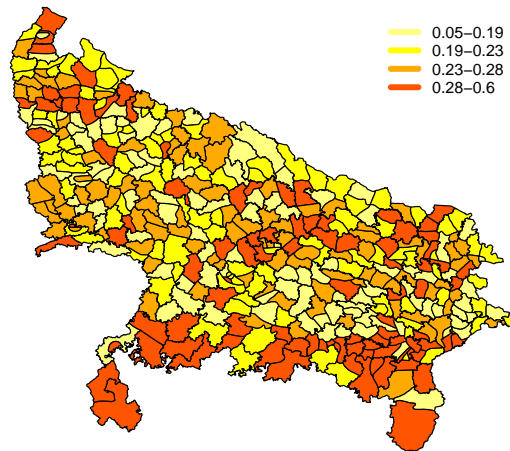
We control for a select set of variables that could influence both the SC population percentage and the probability of RGGVY implementation. Section A1 presents the variables in greater details. For each control variable, we also explain why it is not a “bad control” in that it would be influenced by SC population (Angrist and Pischke, 2009). For summary statistics, see Table A2.

We begin with the logarithmized distance between the village and the closest town. Because all towns in UP are now electrified, the cost and ease of implementing rural electrification works in nearby villages is much lower than the cost of such works in faraway villages. Next, we control for earlier village-level electrification status, as per the 2001 Census of India. Obviously, the status of village electrification in 2001 is a strong predictor for the need for RGGVY. We also control for the logarithmized population of the village. Larger villages tend to have higher electrification rates to begin with, so they may not need the RGGVY. Because RGGVY implementation requires infrastructure, we also control for the presence of a paved road. We include electoral constituency fixed effects in some models. These fixed effects allow us to compare villages close to each other and sharing similar political histories. It also helps us rule out competing explanations for our findings, such as those based on UP’s location with respect to national electricity sources.

Finally, we control for wealth-related confounders in Table A30. One possible source of bias could be that wealthier villages, which tend to have lower SC shares, either have less need for electrification or are electrified first for economic gains. Poverty could thus be simultaneously correlated to policy implementation and SC presence, making our main estimates spurious. While controlling for wealth is difficult because of possible post-treatment bias, we can use data from the pre-RGGVY period to this effect. From the 2001 census, we include an index of wealth built on the share of the population that owns assets such as TVs, cars, radios, and so forth (Filmer and



(a) RGGVY by Constituency



(b) SC Share by Constituency

Figure 1: Geographic distribution of RGGVY implementation and SC share by electoral constituency.

Pritchett, 2001). We also include other wealth proxies such as the village literacy rate (%), the number of cooperative banks, and the (logarithmized) area of irrigated land. We also control for average nighttime luminosity from 1995-2004 using NOAA satellite data (further disaggregation by hamlet is not feasible due to data constraints). Our results remain virtually identical, suggesting that wealth is not biasing our results.

For a more stringent test of caste inequality in policy implementation, we also split the sample by 2001 village electrification status. We first examine whether among villages electrified in 2001, the size of the SC population predicts RGGVY implementation; we then conduct the analysis for villages that were not electrified in 2001. Relatedly, we discuss the relationship between village electrification and SC population *before* the RGGVY begins in Section A2. We show that while villages without Dalits had slightly lower electrification rates pre-RGGVY, this was almost entirely driven by a number of small villages without any Dalits.

5 Caste Inequality in the RGGVY: Findings

We present the main result in three parts. First, we examine whether SC population predicts RGGVY implementation. The second part replicates the analysis separately for previously electrified and non-electrified villages. The final part digs deeper into the consequences of caste inequality.

5.1 Results from the Full Sample

In Table 1 we show the results for the full sample of all UP villages. The upper panel shows the pooled regressions; the lower panel shows the estimates with constituency fixed effects.

The *negative* correlation between the SC percentage and RGGVY implementation at the village level is large and robust. Depending on the model, increasing the SC population by 10 percentage points (1/2 standard deviation) reduces the probability of RGGVY implementation by about two percentage points. Comparing a village populated by Dalits to one without any Dalits, the difference is thus about 20 percentage points – a massive difference, when only 31% of all villages in UP saw RGGVY implementation. The result also cannot be attributed to differences in 2001 village electrification status, as controlling for this variable makes no difference whatsoever.

When we repeat the estimation for the major regions of the state (Western, Central, Eastern,

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.18*** (0.02)	-0.17*** (0.02)	-0.16*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.15*** (0.02)
Distance (log)		3.15*** (0.48)				3.26*** (0.46)
Domestic Electricity (2001)			-0.16*** (0.01)			-0.14*** (0.01)
Population (log)				-6.53*** (0.50)		-5.67*** (0.49)
Pucca Road					-6.48*** (0.99)	-3.59*** (0.96)
Constant	35.43*** (1.33)	27.86*** (1.61)	40.64*** (1.47)	80.42*** (3.98)	39.60*** (1.35)	73.64*** (4.13)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.03	0.03	0.01	0.06
# Clusters	402	401	402	402	402	401
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.21*** (0.01)	-0.21*** (0.01)	-0.20*** (0.01)	-0.20*** (0.01)	-0.21*** (0.01)	-0.19*** (0.01)
Distance (log)		1.35*** (0.22)				1.10*** (0.21)
Domestic Electricity (2001)			-0.15*** (0.01)			-0.13*** (0.01)
Population (log)				-6.64*** (0.40)		-5.93*** (0.38)
Pucca Road					-5.44*** (0.47)	-2.34*** (0.42)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.04	0.04	0.01	0.06
# Clusters	402	401	402	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Dependent variable: RGGVY (if present, RGGVY= 100). The standard errors are clustered by constituency.

	Unelectrified in 2001					Electrified in 2001				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share SC (%)	-0.20*** (0.01)	-0.20*** (0.01)	-0.19*** (0.01)	-0.20*** (0.01)	-0.19*** (0.01)	-0.17*** (0.01)	-0.17*** (0.01)	-0.17*** (0.01)	-0.17*** (0.01)	-0.17*** (0.01)
Distance (log)		1.49*** (0.26)			1.34*** (0.26)		0.54** (0.22)			0.52** (0.22)
Population (log)			-6.08*** (0.40)		-5.86*** (0.41)			-4.73*** (0.41)		-4.65*** (0.43)
Pucca Road				-6.11*** (0.55)	-3.18*** (0.52)				-1.67*** (0.57)	-0.13 (0.58)
Observations	61951	58246	61951	61724	58104	34606	32437	34606	34472	32350
R ²	0.01	0.01	0.03	0.01	0.03	0.01	0.01	0.02	0.01	0.02
# Clusters	402	401	402	401	400	397	397	397	397	397
Constituency FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Dependent variable: RGGVY (if present, RGGVY= 100). All models estimated with constituency fixed effects. The standard errors are clustered by constituency.

and Bundelkhand), we see evidence of inequality in all four areas (Section A8). This not only demonstrates the robustness of the main result, but also shows that major differences in socio-economic characteristics do not seem to eradicate inequality. In fact, the relatively wealthy western parts and the poor Bundelkhand region have the strongest negative associations between SC share and the likelihood of RGGVY implementation.

5.2 Split Samples

Table 2 shows the estimates separately for villages that were or were not electrified according to the 2001 Census of India. All models are estimated with constituency fixed effects. As the table shows, the result does not depend on prior electrification status. Regardless of whether a village was electrified in 2001 or not, increasing SC population by ten percentage points reduces the probability of RGGVY implementation by about two percentage points. Importantly, this lack of difference allows us to rule out the possibility that the positive association between Dalit population and village electrification in the 2001 Census of India would confound our estimates.

5.3 Consequences of Caste Inequality

In Table 3, we summarize the consequences of caste inequality by replacing RGGVY implementation with the percentage of electrified households in the 2011 Census of India. The various models reveal the cost of caste inequality to the SC population: as the SC share of a village increases by ten percentage points, the village electrification rate decreases by about 1 percentage point. Thus, a comparison of a Dalit village to one without any Dalits would thus show a difference of 10

percentage points.

We confirm these findings with survey data from Aklin, Cheng, Urpelainen, Ganesan, and Jain (2016). Table A45 shows that Dalit households are 15 percentage points less likely to have grid electricity connections, again consistent with the notion that the lack of RGGVY implementation is hurting Dalit households.

6 Political Mobilization against Inequality: Research Design

We now turn to the second part of our inquiry: can political mobilization in UP reduce caste inequality? We conduct a regression discontinuity analysis.

6.1 Sample and Model

The basic unit is now a village-election (elections were held in 2002 and 2007) and the outcome a binary indicator for RGGVY implementation. The treatment is assigned at the constituency-election level: did a BSP candidate win against a non-BSP candidate by a narrow margin? We map villages into constituencies by using official delimitation lists from Jensenius (2015) that allow us to link every village in UP to a unique constituency.¹⁰

We estimate models at the 1%, 2%, and 5% margin of victory. Larger bandwidths benefit from stronger statistical power, but at the cost of more potential for bias. The Imbens and Kalyanaraman (2012) test of optimal bandwidth suggest that the best margin is about 3.2, and the results also hold with this bandwidth. For discontinuity plots, see Figures A7-A9; for additional bandwidths, see A20.

Let i denote a village, j a constituency, and k an election period (either after 2002 or after 2007 elections). The estimation equation can be written as follows:

$$Y_{ijk} = \alpha + \beta_1 \text{BSP}_{jk} + \beta_2 \text{SC}_{ij} + \beta_3 \text{BSP} * \text{SC}_{ijk} + \mathbf{X}'_{ijk} \gamma + \epsilon_{ijk}, \quad (2)$$

where Y_{ijk} is again the dependent variable, SC the relevant population percentage, and BSP an indicator for the party's electoral victory. The vector of control variables now includes the for-

¹⁰India's constituency boundaries were redrawn in the 2008 delimitation, but these changes applied in UP for the first time in the 2012 election.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.09*** (0.01)	-0.09*** (0.01)	-0.09*** (0.01)	-0.09*** (0.01)	-0.09*** (0.01)	-0.09*** (0.01)
Distance (log)		-2.13*** (0.24)				-2.15*** (0.24)
Domestic Electricity (2001)			0.00 (0.00)			0.00 (0.00)
Population (log)				-0.73*** (0.27)		-0.96*** (0.27)
Pucca Road					0.86 (0.68)	1.44** (0.71)
Constant	25.57*** (0.73)	30.66*** (0.99)	25.53*** (0.77)	30.59*** (1.86)	25.05*** (0.82)	36.30*** (1.99)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.02	0.01	0.01	0.01	0.02
# Clusters	402	401	402	402	402	401
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.08*** (0.01)	-0.09*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.09*** (0.01)
Distance (log)		-1.52*** (0.13)				-1.54*** (0.13)
Domestic Electricity (2001)			0.01*** (0.00)			0.01*** (0.00)
Population (log)				-0.77*** (0.18)		-0.97*** (0.18)
Pucca Road					0.74*** (0.21)	1.16*** (0.22)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.01	0.01	0.01	0.02
# Clusters	402	401	402	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Dependent variable: household electrification in 2011 (0-100 percent). The standard errors are clustered by constituency.

ing variable, that is, the margin of victory of BSP victory (negative when BSP barely loses) in percentages of valid votes.¹¹

Standard errors are conservatively clustered by constituency throughout. Because there were two elections (2002, 2007) between the 2001 and 2011 Censuses in UP, each village appears in the dataset twice, once for each election.¹² The clustering of standard errors ensures that this procedure does not result in double-counting of observation and thus the artificial deflation of standard errors (e.g., Folke, 2014).¹³

6.2 Explanatory Variable

The primary explanatory variable is a BSP victory in close elections. Because BSP portrays itself as the party of the Dalits and other oppressed people, it is the primary mode of political mobilization against caste inequality in UP. Because BSP victory can be considered quasi-random in close elections, we can use it to identify the effect of this kind of political mobilization on inequality.

In some models, we interact the treatment with the SC percentage in a village. If BSP truly protects SC populations, then electing a BSP MLA should have a particularly large positive effect on RGGVY implementation in villages with a large SC population.

We also estimate models with a triple interaction between BSP win, SC share, and an indicator for an SC-reserved constituency. This test allows us to investigate whether a BSP win has differential effects when the candidates must be from the scheduled castes. The difference might be negative if SC candidates from non-BSP are sympathetic to the plight of the lower castes; or might be positive if it ensures that the BSP MLA is actually himself or herself from a scheduled caste.

Figure A4 shows the margin of victory for each constituency-election in the RDD sample (5% margin of victory). Table A9, in turn, summarizes the sample for the RDD analysis. In total, we have 235 close constituency-elections when the sample is restricted to a 5% margin of victory. Finally, table A10 compares BSP and non-BSP MLAs. As the table shows, both the candidate and

¹¹We do not include fixed effects to avoid the problem of incidental parameters. Given the discontinuity design, fixed effects are not necessary for identification.

¹²We do not use data from the 2012 election because we lack electrification outcomes at the village levels after the 2011 Census.

¹³We also clustered standard errors at the district level in Tables A39 to A41. This would account for correlation within entire districts. Likewise, we estimate spatial autoregressive models in Tables A42 and A43, which report the effect of SC presence on a state-by-state basis. The results remain very similar to our main estimates.

constituency characteristics are mostly similar. The only exception – an unsurprising one – is that BSP MLAs tend to come from SC-reserved constituencies.

Tests of the identifying assumptions are found in Section A3. We find balance over pre-treatment covariates across samples. Similarly, following McCrary (2008), we find no suspicious discontinuity, alleviating concerns about electoral fraud and other irregularities.

7 Political Mobilization against Caste Inequality: Results

Table 4 shows the RDD results without the product term for heterogeneous effects depending on the village SC percentage. BSP victory has no systematic effect on the probability of RGGVY implementation. The coefficients are sometimes positive and sometimes negative, but always relatively small and never statistically significant. While lack of significance could be a statistical power issue, the confidence interval suggest a weak effect regardless. Even if the largest positive coefficients were correct, they would not offset the large difference of 20 percentage points between villages with only and no Dalits at all.

In Table 5, we include the product term of BSP victory and the village SC percentage; the table is otherwise similar to the previous one. Again, we see little evidence for the positive effects of BSP electoral victories in reducing caste inequality. The coefficient for BSP victory still exhibits sign flips, and the coefficient for the product term is small and statistically insignificant. At the same time, SC percent continues to exhibit a strong negative effect on RGGVY implementation.

In Table A15, we estimate the correlation between a BSP victory and RGGVY implementation in the full sample. While the coefficient is not identified, it gives us a sense of the external validity of the null result and ensures that our results are not driven by high degrees of electoral competitiveness. As the table shows, the full sample correlation is similar to the identified coefficient in the RDD: BSP victories are, again, not associated with variation in RGGVY implementation.

In Table A31, we rule out the possibility that the BSP null result can be explained by selective targeting of core or swing voters. We examine the subset of electoral constituencies that have witnessed a BSP victory, and see whether the MLA's margin of victory conditions the association between village SC share and RGGVY implementation. We find that margin of victory is irrelevant, suggesting that the null result holds in both core and swing constituencies. This is consistent with

	Margin < 1%			Margin < 2%			Margin < 5%					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BSP Win	3.08 (4.90)	3.05 (4.88)	7.77 (11.44)	8.15 (11.87)	-2.94 (4.51)	-2.94 (4.50)	8.32 (7.46)	8.58 (7.59)	-0.86 (3.23)	-0.89 (3.23)	1.23 (5.26)	1.10 (5.25)
2007 Election		-0.78 (4.93)	-0.73 (4.93)	-0.32 (4.92)		-2.77 (4.58)	-2.54 (4.49)	-1.89 (4.61)		0.42 (2.48)	0.49 (2.47)	0.43 (2.45)
BSP Margin		-5.31 (9.99)	-5.31 (9.99)	0.13 (7.82)		-5.83 (7.82)	-5.83 (3.64)	-3.84 (5.06)			-0.45 (0.96)	0.40 (1.48)
BSP Win * Margin				-11.10 (20.38)				-4.24 (7.33)				-1.63 (1.85)
Constant	28.93*** (2.39)	29.34*** (3.22)	27.10*** (4.82)	29.26*** (4.70)	32.47*** (3.27)	34.11*** (4.48)	28.39*** (4.59)	29.92*** (4.73)	30.88*** (2.53)	30.65*** (3.04)	29.55*** (3.42)	31.59*** (4.07)
Observations	14086	14086	14086	14086	26793	26793	26793	26793	62079	62079	62079	62079
R ²	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00
# Clusters	55	55	55	55	97	97	97	97	200	200	200	200

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: RDD analysis with BSP victory effects: 1%, 2%, 5% bandwidths. Dependent variable: RGGVY (if present, RGGVY = 100). The standard errors are clustered by constituency.

	Margin < 1%			Margin < 2%			Margin < 5%					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BSP Win	1.75 (5.24)	1.76 (5.31)	6.84 (11.49)	7.36 (11.86)	-4.58 (5.13)	-4.58 (5.14)	5.85 (7.45)	5.89 (7.46)	-0.06 (3.90)	-0.05 (3.90)	1.56 (5.50)	1.26 (5.47)
BSP Win * Share SC	0.03 (0.09)	0.03 (0.08)	0.01 (0.08)	0.01 (0.08)	0.06 (0.06)	0.06 (0.06)	0.05 (0.06)	0.06 (0.06)	-0.02 (0.05)	-0.02 (0.05)	-0.02 (0.05)	-0.02 (0.05)
Share SC (%)	-0.25*** (0.06)	-0.25*** (0.06)	-0.25*** (0.06)	-0.25*** (0.06)	-0.27*** (0.05)	-0.28*** (0.05)	-0.26*** (0.04)	-0.27*** (0.04)	-0.19*** (0.04)	-0.19*** (0.04)	-0.19*** (0.04)	-0.20*** (0.04)
2007 Election	-2.14 (4.86)	-2.14 (4.86)	-2.11 (4.86)	-1.88 (4.85)	-3.46 (4.53)	-3.46 (4.53)	-3.22 (4.46)	-2.52 (4.56)	-0.04 (2.47)	-0.04 (2.47)	0.01 (2.44)	-0.06 (2.44)
BSP Margin			-5.39 (10.03)	1.49 (8.09)	-5.25 (3.64)	-5.25 (3.64)	-3.07 (4.61)	-3.07 (4.61)	-0.33 (0.96)	-0.33 (0.96)	0.61 (1.47)	0.61 (1.47)
BSP Win * Margin			-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)	-14.06 (20.43)
Constant	35.57*** (3.36)	36.82*** (4.13)	34.41*** (5.68)	37.34*** (5.68)	39.45*** (3.95)	41.64*** (5.01)	36.04*** (4.90)	37.85*** (4.95)	35.62*** (3.05)	35.65*** (3.51)	34.79*** (3.75)	37.17*** (4.29)
Observations	14086	14086	14086	14086	26793	26793	26793	26793	62079	62079	62079	62079
R ²	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01
# Clusters	55	55	55	55	97	97	97	97	200	200	200	200

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: RDD analysis with BSP victory effects conditional on SC share: 1%, 2%, 5% bandwidths. Dependent variable: RGGVY (if present, RGGVY = 100). The standard errors are clustered by constituency.

our simple caste inequality hypothesis.

Likewise, we can rule out that electing SC representatives (in contrast to a BSP representative) does not help either. In Table A21, we show that the RD estimates when looking at SC winners yields similarly small and insignificant estimates.

To summarize, our evidence suggests that BSP mobilization has not reduced bias against Dalits in RGGVY implementation. Across different bandwidths and regardless of whether we condition the effect of BSP victory on SC share, there is no evidence of this kind of political mobilization changing outcomes. Although the BSP claimed to protect Dalit interests and put together schemes such as Ambedkar villages on paper, these schemes appear not to have done anything to reduce the bias against Dalit communities in the national rural electrification program.

In Section A7, we report the results when conditioning the interactive effect of SC share and BSP win on reservation status. Overall, we see no evidence of differential effects: regardless of whether we use split samples or a triple interaction term, BSP wins do not benefit the scheduled castes in reserved or non-reserved constituencies.

Table 6 offers a possible explanation to the conundrum. In this table, we code the caste characteristics of winning candidates in reserved and unreserved MLA constituencies. As we can see, there are virtually no SC politicians outside reserved constituencies. Thus, even where BSP wins seats, the candidates themselves are mostly not Dalits. Although the BSP presents itself as a pro-Dalit party, it relies on non-Dalit candidates unless electoral quotas force the party leaders to choose Dalit candidates.

8 Conclusion

Public policies play an important role in poverty alleviation. However, unequal policy implementation threatens to exclude vulnerable minority groups from these gains. Here we have documented widespread inequality in the implementation of India's flagship rural electrification initiative, the RGGVY, in UP. For every additional percentage point of Dalits in the village population, the probability of RGGVY coverage decreases by 0.15-0.20 percentage points, resulting in massive differences between Dalit and non-Dalit villages. Such differences cannot be attributed to plausible alternative explanations, such as poverty or a lack of collective action. Although BSP, a Dalit

Type of seat	2002	2007
Among all MLAs		
General seat	4.1% (n=292)	1.4% (n=293)
Reserved seat	94.1% (n=85)	94.2% (n=86)
Among BSP MLAs		
General seat	2.9% (n=68)	2.2% (n=133)
Reserved seat	95.7% (n=23)	91.4% (n=58)

Table 6: Share of MLAs from SC background by type of constituency. The data was coded based on the caste connotation of Hindi-language family names, online sources for winning candidates, and phone conversations with local journalists covering politics. The coding was done by native Hindi speakers in Lucknow, the capital of UP. In reserved constituencies, the percentages likely fall below 100% because some candidate names cannot be unambiguously ascribed to a specific caste group.

party, has enjoyed considerable electoral success in UP over the past two decades, our regression discontinuity analysis also shows that this success has not reduced caste inequality. A plausible explanation for this failure is that most BSP politicians are in fact not themselves Dalits.

Our study has several policy implications. One is to highlight the limits of legislative oversight and political representation to curb discrimination. Instead, it appears that some of the problems raised here stem from the freedom that local officials have to implement policies. The freedom generated by a bottom-up approach is valuable in many settings. However, when it overlaps with social cleavages, it opens up the possibility of discriminatory implementation. This problem could be addressed in two steps. *Ex ante*, policymakers should create clear and transparent criteria that can constrain how program beneficiaries are selected. For instance, population thresholds may be used to identify who should first benefit from a program. *Ex post*, the government should monitor implementation at the micro level to detect discriminatory patterns. A system that rests on guidelines and aggressive monitoring might be more effective than one that depends on sometimes ineffective legislators. Of course, to be clear: this is only likely to work if policymakers do wish to limit discrimination. If they don't, then relying on policy design to address discrimination is unlikely to achieve much.

Biased implementation of public policies presents an important research frontier. Now that inequality in society and markets has been established in numerous studies, the natural next question concerns the extent of bias in public policy and in the design of interventions to reduce such

bias. The generalizability and external validity of our finding warrant further analysis, as we have focused on a specific kind of public service – rural electrification – in the context of rigid caste hierarchies and a central role of the state in policy implementation. Rural electrification itself is a common challenge across most low-income countries, while ethnic hierarchies and inequalities abound across the world. We would expect similar biases to creep into grid extension programs in ethnically segregated societies across the world. Rural electrification through grid extension is also typically a public investment by the state, and thus particularly vulnerable to political and bureaucratic bias. What is more, electoral competition in India often revolves around religious and caste-based concerns.

Examining patterns of inequality and the effectiveness of political mobilization in different contexts, such as privatized service delivery in the urban context or in countries with different logics of electoral competition, seems a natural extension of our approach. While community-level characteristics predict differential levels of access to electric infrastructure, such bias might not be feasible in densely populated urban contexts. Similarly, programmatic political competition between parties could allow political mobilization to be a more effective antidote than in UP caste politics.

The results are normatively troubling. Although India has seven decades of democratic experience and a robust constitution, actual policy implementation remains biased. Even the striking electoral success of a minority party has not reduced such inequality in India's largest state. Despite India's progressive constitutional law and decades of anti-discrimination endeavors following independence, it appears that government policy remains *de facto* biased against the lower castes. If a major rural electrification program is heavily biased against Dalits, then the prospect for eradicating caste stratification and curtailing discrimination against the marginalized segments of the society – at least in the short run – are bleak.

References

- Aklin, Michaël, Chao-yo Cheng, Johannes Urpelainen, Karthik Ganesan, and Abhishek Jain. 2016. “Factors Affecting Household Satisfaction with Electricity Supply in Rural India.” *Nature Energy* 1 (16170).
- Aklin, Michaël, Chao-yo Cheng, Karthik Ganesan, Abhishek Jain, Johannes Urpelainen, and Council on Energy, Environment and Water. 2016. “Access to Clean Cooking Energy and Electricity: Survey of States in India (ACCESS).” Harvard Dataverse, V1. <http://dx.doi.org/10.7910/DVN/0NV9LF>.
- Alesina, Alberto, and Eliana La Ferrara. 2011. “A Test of Racial Bias in Capital Sentencing.” *American Economic Review* 104 (11): 3397-3433.
- Alsop, Ruth, Mette Frost Bertelsen, and Jeremy Holland. 2006. *Empowerment in Practice: From Analysis to Implementation*. Washington DC: World Bank.
- Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist’s Companion*. Princeton: Princeton University Press.
- Arrow, Kenneth J. 1998. “What Has Economics to Say about Racial Discrimination?” *Journal of Economic Perspectives* 12 (2): 91-100.
- Asher, Sam, and Paul Novosad. 2017. “Politics and Local Economic Growth: Evidence from India.” *American Economic Journal: Applied Economics* 9 (1).
- Ayres, Ian, and Peter Siegelman. 1995. “Race and Gender Discrimination in Bargaining for a New Car.” *American Economic Review* 85 (3): 304-321.
- Banerjee, Abhijit, Lakshmi Iyer, and Rohini Somanathan. 2005. “History, Social Divisions, and Public Goods in Rural India.” *Journal of the European Economic Association* 3 (2-3): 639-647.
- Banerjee, Abhijit, Marianne Bertrand, Saugato Datta, and Sendhil Mullainathan. 2009. “Labor Market Discrimination in Delhi: Evidence from a Field Experiment.” *Journal of Comparative Economics* 37 (1): 14-27.

- Bayly, Susan. 2001. *Caste, Society and Politics in India from the Eighteenth Century to the Modern Age*. New York: Cambridge University Press.
- Becker, Gary S. 1957. *The Economics of Discrimination*. Chicago: University of Chicago Press.
- Bertrand, Marianne, and Sendhil Mullainathan. 2004. "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review* 94 (4): 991-1013.
- Bhavnani, Rikhil R. 2017. "Do the Effects of Temporary Ethnic Group Quotas Persist? Evidence from India." *American Economic Journal: Applied Economics* 9 (3): 105-123.
- Bose, Sumantra. 2013. *Transforming India: Challenges to the World's Largest Democracy*. Cambridge: Harvard University Press.
- Bros, Catherine, and Mathieu Couttenier. 2010. "Untouchability And Public Infrastructure." Documents de travail du Centre d'Economie de la Sorbonne 2010.74.
- Bullard, Robert D. 1990. *Dumping in Dixie: Race, Class, and Environmental Quality*. Boulder: Westview Press.
- Burlig, Fiona, and Louis Preonas. 2016. "Out of the Darkness and Into the Light? Development Effects of Rural Electrification in India." Energy Institute at Haas, Working Paper 268. <https://ei.haas.berkeley.edu/research/papers/WP268Appendix.pdf>.
- Butler, Daniel M., and David E. Broockman. 2011. "Do Politicians Racially Discriminate Against Constituents? A Field Experiment on State Legislators." *American Journal of Political Science* 55 (3): 463-477.
- Chandra, Kanchan. 2007. *Why Ethnic Parties Succeed: Patronage and Ethnic Head Counts in India*. New York: Cambridge University Press.
- Chauchard, Simon. 2014. "Can Descriptive Representation Change Beliefs about a Stigmatized Group? Evidence from Rural India." *American Political Science Review* 108 (2): 403-422.

- Chauchard, Simon. 2017. *Why Representation Matters: The Meaning of Ethnic Quotas in Rural India*. New York: Cambridge University Press.
- Chen, Elsa Y. 2013. "Is All Punishment Local? The Effects of Jurisdictional Context on Sentence Length." *Social Science Quarterly* 94 (5): 1372-1397.
- Chhibber, Pradeep, and Irfan Nooruddin. 2004. "Do Party Systems Count? The Number of Parties and Government Performance in the Indian States." *Comparative Political Studies* 37 (2): 152-187.
- Chopra, Vir K. 1996. *Marginal Players in Marginal Assemblies: The Indian MLA*. New Delhi: Orient Longman.
- Corbridge, Stuart, Glyn Williams, Manoj Srivastava, and Rene Veron. 2005. *Seeing the State: Governance and Governmentality in India*. Cambridge: Cambridge University Press.
- Deshpande, Ashwini. 2000. "Does Caste Still Define Disparity? A Look at Inequality in Kerala, India." *American Economic Review* 90 (2): 322-325.
- Dhar, Diva, Tarun Jain, and Seema Jayachandran. 2018. "Reshaping Adolescents' Gender Attitudes: Evidence from a School-Based Experiment in India." NBER Working Paper.
- Distelhorst, Greg, and Yue Hou. 2014. "Ingroup Bias in Official Behavior: A National Field Experiment in China." *Quarterly Journal of Political Science* 9: 203-220.
- Drèze, Jean, and Amartya K. Sen. 2002. *India: Development and Participation*. New York: Oxford University Press. 2nd Edition.
- Dugoua, Eugenie, Ryan Kennedy, and Johannes Urpelainen. 2018. "Satellite data for the social sciences: measuring rural electrification with night-time lights." *International Journal of Remote Sensing* 39 (9): 2690-2701.
- Duncan, Ian. 1999. "Dalits and Politics in Rural North India: The Bahujan Samaj Party In Uttar Pradesh." *Journal of Peasant Studies* 27 (1): 35-60.

- Dunning, Thad, and Janhavi Nilekani. 2013. "Ethnic Quotas and Political Mobilization: Caste, Parties, and Distribution in Indian Village Councils." *American Political Science Review* 107 (1): 35-56.
- Dynes, Adam M., and Gregory A. Huber. 2015. "Partisanship and the Allocation of Federal Spending: Do Same-Party Legislators or Voters Benefit from Shared Party Affiliation with the President and House Majority?" *American Political Science Review* 109 (1): 172-186.
- Einstein, Katherine Levine, and David M. Glick. 2016. "Does Race Affect Access to Government Services? An Experiment Exploring Street-Level Bureaucrats and Access to Public Housing." *American Journal of Political Science*.
- Filmer, Deon, and Lant H. Pritchett. 2001. "Estimating Wealth Effects without Expenditure Data—or Tears: An Application to Educational Enrollments in States of India." *Demography* 38 (1): 115-132.
- Folke, Olle. 2014. "Shades of Brown and Green: Party Effects in Proportional Election Systems." *Journal of the European Economic Association* 12 (5): 1361-1395.
- Franck, Raphael, and Ilia Rainer. 2012. "Does the Leader's Ethnicity Matter? Ethnic Favoritism, Education, and Health in Sub-Saharan Africa." *American Political Science Review* 106 (2): 294-325.
- Government of India. 2013. "Primary Census Abstract." Data Highlights. http://idsn.org/wp-content/uploads/user_folder/pdf/New_files/India/2013/INDIA_CENSUS_ABSTRACT-2011-Data_on_SC-STs.pdf.
- Greenpeace. N.d. "Rajiv Gandhi Grameen Vidyutikaran Yojana Social Survey Report." March-April 2011,.
- Guryan, Jonathan, and Kerwin Kofi Charles. 2013. "Taste-Based or Statistical Discrimination: The Economics of Discrimination Returns to Its Roots." *Economic Journal* 123 (572): F417-F432.

- Hasan, Zoya. 2009. *Politics of Inclusion: Caste, Minority, and Representation in India*. New Delhi: Oxford University Press.
- Imbens, Guido W., and K. Kalyanaraman. 2012. "Optimal Bandwidth Choice for the Regression Discontinuity Estimator." *Review of Economic Studies* 79 (3): 933-959.
- IRADe. 2013. "Final Report on Evaluation of Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY) in Rajasthan, Assam, Gujarat, Himachal Pradesh and Uttar Pradesh." Integrated Research and Action for Development, New Delhi. http://www.ddugjy.gov.in/mis/portal/evaluation/IRADe_Combined_Executive_Summary.pdf.
- Iyer, Lakshmi, and Anandi Mani. 2012. "Traveling Agents: Political Change and Bureaucratic Turnover in India." *Review of Economics and Statistics* 94 (3): 723-739.
- Jaffrelot, Christophe. 2003. *India's Silent Revolution: The Rise of the Lower Castes in North India*. New York: Columbia University Press.
- Jaffrelot, Christophe. 2006. "The Impact of Affirmative Action in India: More Political Than Socioeconomic." *India Review* 5 (2): 173-189.
- Jaoul, Nicolas. 2006. "Learning the Use of Symbolic Means Dalits, Ambedkar Statues and the State in Uttar Pradesh." *Contributions to Indian Sociology* 40 (2): 175-207.
- Jeffrey, Craig, Patricia Jeffery, and Roger Jeffery. 2008. "Dalit Revolution? New Politicians in Uttar Pradesh, India." *Journal of Asian Studies* 67 (4): 1365-1396.
- Jensenius, Francesca Refsum. 2015. "Development from Representation? A Study of Quotas for Scheduled Castes in India." *American Economic Journal: Applied Economics* 7 (3): 196-220.
- Kaas, Leo, and Christian Manger. 2012. "Ethnic Discrimination in Germany's Labour Market: A Field Experiment." *German Economic Review* 13 (1): 1-20.
- Kale, Sunila S. 2014. "Structures of Power: Electrification in Colonial India." *Comparative Studies of South Asia, Africa and the Middle East* 34 (3): 454-475.

- Kapur, Devesh, Chandra Bhan Prasad, Lant Pritchett, and D. Shyam Babu. 2010. "Rethinking Inequality: Dalits in Uttar Pradesh in the Market Reform Era." *Economic and Political Weekly* 45 (35): 39-49.
- Khandker, Shahidur R., Douglas F. Barnes, and Hussain A. Samad. 2013. "Welfare Impacts of Rural Electrification: A Panel Data Analysis from Vietnam." *Economic Development and Cultural Change* 61 (3): 659-692.
- Khandker, Shahidur R., Douglas F. Barnes, Hussain Samad, and Nguyen Huu Minh. 2009. "Welfare Impacts of Rural Electrification: Evidence from Vietnam." World Bank Policy Research Working Paper 5057.
- Kruks-Wisner, Gabrielle. 2018. *Claiming the State: Active Citizenship and Social Welfare in Rural India*. New York: Cambridge University Press.
- Louis, Prakash. 2003. *The Political Sociology of Dalit Assertion*. New Delhi: Gyan Publishing House.
- Lovell, Peggy A. 1993. "The Geography of Economic Development and Racial Discrimination in Brazil." *Development and Change* 24 (1): 83-102.
- McClendon, Gwyneth H. 2016. "Race and Responsiveness: An Experiment with South African Politicians." *Journal of Experimental Political Science* 3 (1).
- McCrary, Justin. 2008. "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test." *Journal of Econometrics* 142 (2): 698-714.
- Mehrotra, Santosh. 2006. "Well-Being and Caste in Uttar Pradesh: Why UP Is Not like Tamil Nadu." *Economic and Political Weekly* 41 (40): 4261-4271.
- Mendelsohn, Oliver, and Marika Vicziany. 1998. *The Untouchables: Subordination, Poverty and the State in Modern India*. Vol. 4 New York: Cambridge University Press.
- Min, Brian. 2015. *Power and the Vote: Elections and Electricity in the Developing World*. New York: Cambridge University Press.

- Ministry of Power. 2006. "Rural Electrification Policy." *Gazette of India* 44/26/05-RE (Vol-II).
- Ministry of Power. 2009. "Implementation Of Rajiv Gandhi Grameen Vidyutikaran Yojana." Thirty-First Report, Standing Committee on Energy, Fourteenth Lok Sabha. <http://www.indiaenvironmentportal.org.in/files/31stReportRGGVY.pdf>.
- Ministry of Power. 2013. "Implementation of Rajiv Gandhi Grameen Vidyutikaran Yojana." Forty-First Report, Standing Committee on Energy, (2013-2014) Fifteenth Lok Sabha, Ministry of Power, New Delhi, India. <http://www.indiaenvironmentportal.org.in/files/file/Implementation%20of%20RGGVY.pdf>.
- Oliver, J. Eric, and Janelle Wong. 2003. "Intergroup Prejudice in Multiethnic Settings." *American Journal of Political Science* 47 (4): 567–582.
- Pai, Sudha. 2001. "Theory and Practice of BSP's Concept of Social Justice: Implications for Politics." In *Protective Discrimination: Ideology and Praxis*, ed. A.K. Lal. New Delhi: Concept Publishing.
- Pai, Sudha. 2004. "Dalit Question and Political Response: Comparative Study of Uttar Pradesh and Madhya Pradesh." *Economic and Political Weekly* 39 (11): 1141-1150.
- Pai, Sudha. 2014. "Understanding the Defeat of the BSP in Uttar Pradesh: National Election 2014." *Studies in Indian Politics* 2 (2): 153-167.
- Pande, Rohini. 2003. "Can Mandated Political Representation Increase Policy Influence for Disadvantaged Minorities? Theory and Evidence from India." *American Economic Review* 93 (4): 1132-1151.
- Posner, Daniel N., and Eric Kramon. 2013. "Who Benefits from Distributive Politics? How the Outcomes One Studies Affect the Answer One Gets." *Perspectives on Politics* 11 (2): 461-474.
- Prayas Energy Group. 2011. "Rajiv Gandhi Rural Electrification Program: Urgent Need for Mid-Course Correction." Discussion Paper.

- Ramaiah, A. 2011. "Growing Crimes Against Dalits in India Despite Special Laws: Relevance of Ambedkars Demand for Separate Settlement." *Journal of Law and Conflict Resolution* 3 (9): 151-168.
- Sen, Maya. 2015. "Is Justice Really Blind? Race and Appellate Review in U.S. Courts." *Journal of Legal Studies* 44 (S1): 187-229.
- Shah, Ghanshyam, Harsh Mander, Sukhadeo Thorat, Satish Deshpande, and Amita Baviskar. 2006. *Untouchability in Rural India*. New Delhi: Sage.
- Sharma, Smriti. 2015. "Caste-based Crimes and Economic Status: Evidence from India." *Journal of Comparative Economics* 43 (1): 204-226.
- Siddique, Zahra. 2011. "Evidence on Caste Based Discrimination." *Labour Economics* 18 (1): S146-S159.
- Singh, Prerna. 2017. *How Solidarity Works for Welfare: Subnationalism and Social Development in India*. New York: Cambridge University Press.
- Smith, Michael Graham, and Johannes Urpelainen. 2016. "Rural Electrification and Groundwater Pumps in India: Evidence from the 1982-1999 Period." *Resource and Energy Economics* 45: 31-45.
- Spears, Dean, and Sneha Lamba. 2013. "Effects of early-life exposure to sanitation on childhood cognitive skills: evidence from India's total sanitation campaign." World Bank Policy Research Working Paper 6659.
- Tajfel, Henri, M. G. Billig, R. P. Bundy, and Claude Flament. 1971. "Social Categorization and Intergroup Behaviour." *European Journal of Social Psychology* 1 (2): 149-178.
- Thorat, Sukhadeo, and Katherine S. Newman. 2007. "Caste and Economic Discrimination: Causes, Consequences and Remedies." *Economic and Political Weekly* 42 (41): 4121-4124.
- Thorat, Sukhadeo and Katherine S. Newman, eds. 2012. *Blocked by Caste: Economic Discrimination in Modern India*. New York: Oxford University Press.

- Thorat, Sukhdeo, and Joel Lee. 2005. "Caste Discrimination and Food Security Programmes." *Economic and Political Weekly* 40 (39): 4198-4201.
- Wade, Robert. 1985. "The Market for Public Office: Why the Indian State Is Not Better at Development." *World Development* 13 (4): 467-497.
- White, Ariel R., Noah L. Nathan, and Julie K. Faller. 2015. "What Do I Need to Vote? Bureaucratic Discretion and Discrimination by Local Election Officials." *American Political Science Review* 109 (1): 129-142.
- Yinger, John. 1997. *Closed Doors, Opportunities Lost: The Continuing Costs of Housing Discrimination*. New York: Russell Sage Foundation.

Supplementary Materials

February 13, 2020

Contents

A1 RGGVY Targeting: Additional Material	APP-2
A1.1 Control Variables and Split Samples	APP-2
A1.2 Summary Statistics	APP-3
A2 Pre-RGGVY Rural Electrification	APP-9
A3 Regression Discontinuity: Identifying Assumptions	APP-13
A4 Regression Discontinuity: Summary Statistics	APP-13
A5 Regression Discontinuity: Balance Statistics and Density Tests	APP-18
A6 Regression Discontinuity: Additional Analysis	APP-23
A7 Regression Discontinuity: Conditioning on Reservation Status	APP-34
A8 Regional Samples	APP-38
A9 Additional Results	APP-43
A10 ACCESS Survey	APP-59
A10.1 Summary Statistics	APP-59
A10.2 Evidence from Household Surveys	APP-59

A1 RGGVY Targeting: Additional Material

A1.1 Control Variables and Split Samples

Because SC population percentages could be correlated with confounding variables, we control for a select set of variables that could influence both the SC population percentage and the probability of RGGVY implementation. For each control variable, we also explain why it is not a “bad control” in that it would be influenced by SC population (e.g., Angrist and Pischke, 2009). For summary statistics, see Table A2.

We begin with the logarithmized distance between the village and the closest town. Because all towns in Uttar Pradesh are now electrified, the cost and ease of implementing rural electrification works in nearby villages is much lower than the cost of such works in faraway villages. At the same time, the social bias against Dalits in Uttar Pradesh may mean that they tend to live farther away from towns.

Next, we control for earlier village-level electrification status, as per the 2001 Census of India (unfortunately, this earlier census does not contain household electrification percentages by village). Obviously, the status of village electrification in 2001 is a strong predictor for the need for RGGVY. At the same time, the geographic distribution of village electrification turns out to be related to SC percentage in the village population (see below for details).

We also control for the logarithmized population of the village. Larger villages tend to have higher electrification rates to begin with, so they may not need the RGGVY. At the same time, larger villages tend to have more diverse populations, and thus their SC shares are much less likely to be zero than those of smaller villages.

Because RGGVY implementation requires infrastructure, we also control for the presence of a paved road. Given that Dalits historically tend to live in more remote and poorly connected villages, the presence of a paved road is also correlated with the SC population.

We include electoral constituency fixed effects in some models. These fixed effects allow us to compare villages close to each other and sharing similar political histories. It also helps us rule out competing explanations for our findings, such as those based on Uttar Pradesh’s location with

Variable	Description	Source
RGGVY	Implementation of RGGVY (= 1) between April 2005 and Oct. 2014	Rural Electrification Corporation of India
Electricity	Percentage of households with grid electricity access as of 2011 (and 2001)	Census 2011
Domestic Electricity (2001)	Village is electrified as of 2001 (= 1)	Census 2001
Share SC	Share of a village's population who belongs to SC (or ST) as of 2011 (and 2001)	Census 2011 (and 2001)
Pucca Road	Indicator denoting the presence of a pucca road (= 1)	Census 2011
Distance (log)	Log distance between the village and the closest towns	Census 2011
Population (log)	Log population of the village	Census 2011
Literacy Rate (%)	Village literacy rate (%)	Census 2001
# Coop Commercial Banks	Number of cooperative banks	Census 2001
Irrigated Land (log)	Log area of irrigated land	Census 2001
Mean Light	Average nighttime luminosity, 1995-2004	NOAA satellite data
BSP Win	BSP won this constituency (= 1)	Election Commission of India
BSP Margin	Margin of victory/loss for BSP (= 1)	Election Commission of India
Caste background of MLA	Whether an MLA is SC or not	Authors' own data

Table A1: Data sources.

respect to national electricity sources.

A1.2 Summary Statistics

- Table A2 shows the summary statistics for the full sample at the village level.
- Tables A3 and A3 show the summary statistics for the full sample by districts for the presence of SCs.
- Tables A5 and A5 show the summary statistics for the full sample by districts for the implementation of RGGVY.

	Summary Statistic				
	Mean	S.D.	Min.	Max	Obs.
RGGVY	31.08	46.28	0	100	96557
Domestic Electricity (2001)	35.84	47.95	0	100	96557
Lighting Source: Electricity	23.41	24.02	0	100	96557
Share SC (%)	24.57	20.70	0	100	96557
BSP Margin	-0.83	8.62	-49	22	52833
BSP Win	0.26	0.44	0	1	96557
Population (log)	6.91	1.10	1	11	96557
Distance (log)	2.43	1.10	0	5	90683
Pucca Road	0.66	0.47	0	1	96196
Lack of Asset	10.94	10.24	0	100	96557
Literacy Rate (%)	55.75	11.19	0	100	96557

Table A2: Summary statistics for the entire sample. The unit of analysis is a village.



Figure A1: Geographic distribution of SC share by village.

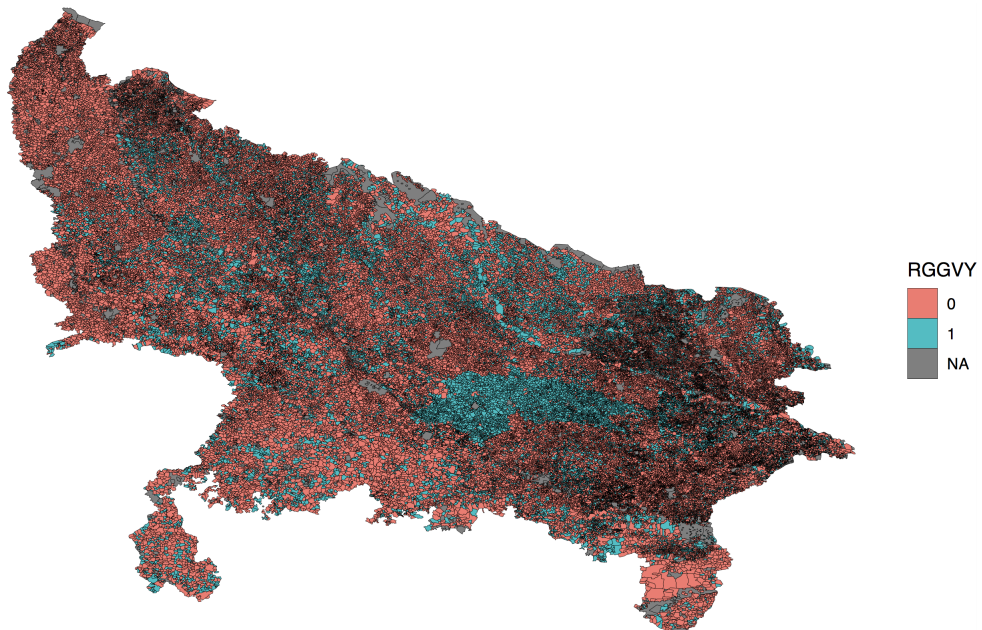


Figure A2: Geographic distribution of RGGVY implementation at the village level.

Summary Statistic: SC/ST by District (part A)

	mean	p25	p50	p75	min	max
Agra	21.6	9.0	19.0	30.4	0.0	98.7
Aligarh	23.8	11.4	21.1	32.5	0.0	100.0
Allahabad	25.3	12.1	23.0	34.6	0.0	100.0
Ambedkar Nagar	28.4	16.2	26.8	38.1	0.0	100.0
Auraiya	30.7	15.7	28.0	42.5	0.0	100.0
Azamgarh	27.5	7.2	23.2	39.6	0.0	100.0
Baghpat	13.1	6.4	11.7	16.9	0.0	73.3
Bahraich	16.4	6.9	12.9	22.3	0.0	97.2
Ballia	18.4	0.9	14.0	27.0	0.0	100.0
Balrampur	16.2	7.7	13.2	20.3	0.0	100.0
Banda	22.2	11.3	20.3	31.2	0.0	99.3
Barabanki	30.6	17.4	28.9	41.2	0.0	100.0
Bareilly	16.3	3.0	11.6	23.3	0.0	100.0
Basti	21.8	8.5	19.5	30.8	0.0	100.0
Bijnor	26.6	2.9	22.2	41.9	0.0	100.0
Budaun	18.3	3.0	13.2	26.2	0.0	100.0
Bulandshahar	23.6	9.8	20.4	33.1	0.0	100.0
Chandauli	28.0	6.9	23.9	40.3	0.0	100.0
Chitrakoot	28.6	14.0	25.3	37.1	0.0	100.0
Deoria	20.4	8.4	17.7	27.5	0.0	100.0
Etah	17.9	3.8	13.5	26.0	0.0	100.0
Etawah	26.5	11.6	23.1	38.0	0.0	100.0
Faizabad	24.5	14.7	22.8	32.1	0.0	99.9
Farrukhabad	17.1	5.2	13.1	24.2	0.0	100.0
Fatehpur	27.3	15.6	25.8	37.1	0.0	100.0
Firozabad	19.7	4.3	15.9	28.5	0.0	100.0
Gautam Buddha Nagar	20.2	8.0	17.6	26.9	0.0	95.4
Ghaziabad	21.1	8.0	18.0	30.2	0.0	100.0
Ghazipur	22.4	0.0	16.8	33.4	0.0	100.0
Gonda	17.5	8.4	15.2	23.3	0.0	100.0
Gorakhpur	25.4	8.0	21.0	35.9	0.0	100.0
Hamirpur	22.4	13.5	22.1	30.0	0.0	100.0
Hardoi	33.0 _{APP-5}	14.7	29.6	47.9	0.0	100.0
Hathras	27.6	12.7	24.4	37.2	0.0	100.0

Table A3: Summary statistics on the presence of SC, by district.

Summary Statistic: SC/ST by District (part B)

	mean	p25	p50	p75	min	max
Jalaun	29.2	15.3	28.1	39.6	0.0	100.0
Jaunpur	23.6	6.7	20.4	33.6	0.0	100.0
Jhansi	31.8	21.7	31.6	41.3	0.0	100.0
Jyotiba Phule Nagar	18.9	1.3	12.4	29.1	0.0	100.0
Kannauj	21.0	9.9	18.0	28.2	0.0	100.0
Kanpur Dehat	26.6	13.7	25.4	36.8	0.0	100.0
Kanpur Nagar	28.8	16.4	26.9	38.5	0.0	100.0
Kaushambi	36.8	24.2	35.8	48.3	0.0	100.0
Kheri	33.4	16.8	29.6	44.3	0.0	100.0
Kushinagar	18.6	9.2	16.2	25.3	0.0	100.0
Lalitpur	27.2	16.9	26.3	36.0	0.0	100.0
Lucknow	41.3	27.7	40.3	53.3	0.0	100.0
Mahoba	27.1	18.0	25.8	35.1	0.0	100.0
Mahrajganj	20.1	10.9	18.3	26.8	0.0	96.5
Mainpuri	20.4	6.7	17.4	28.2	0.0	100.0
Mathura	21.1	9.9	17.9	28.7	0.0	100.0
Mau	26.8	2.5	20.6	40.3	0.0	100.0
Meerut	22.4	7.9	19.9	32.4	0.0	100.0
Mirzapur	29.4	9.1	25.3	45.7	0.0	100.0
Moradabad	19.7	2.6	13.8	29.5	0.0	100.0
Muzaffarnagar	18.5	6.1	14.5	24.7	0.0	100.0
Pilibhit	17.0	2.4	12.8	23.8	0.0	100.0
Pratapgarh	22.7	12.4	21.2	30.7	0.0	100.0
Rae Bareli	33.0	22.2	31.7	42.8	0.0	100.0
Rampur	16.6	1.2	8.6	25.3	0.0	100.0
Saharanpur	28.2	10.1	25.4	40.4	0.0	100.0
Sant Kabir Nagar	23.2	8.4	19.5	32.4	0.0	100.0
Sant Ravidas Nagar Bhadohi	22.7	3.5	19.2	33.1	0.0	100.0
Shahjahanpur	20.4	4.4	14.3	28.7	0.0	100.0
Shrawasti	19.6	10.7	17.1	25.3	0.0	99.4
Siddharthnagar	17.8	6.5	14.7	25.0	0.0	100.0
Sitapur	37.8	23.1	36.3	50.1	0.0	100.0
Sonbhadra	43.7	22.0	40.8	64.2	0.0	100.0
Sultanpur	23.8	13.1	22.0	31.8	0.0	100.0
Unnao	36.0	22.3	33.7	47.4	0.0	100.0
Varanasi	18.8	3.6	14.9	27.4	0.0	100.0
Total	24.6	9.0	21.0	34.9	0.0	100.0

Table A4: Summary statistics on the presence of SC, by district.

Summary Statistic: RGGVY by District (Part A)

	Mean	25th pctl	50th pctl	75th pctl	Min	Max
Agra	15.6	0.0	0.0	0.0	0.0	100.0
Aligarh	28.7	0.0	0.0	100.0	0.0	100.0
Allahabad	35.3	0.0	0.0	100.0	0.0	100.0
Ambedkar Nagar	6.8	0.0	0.0	0.0	0.0	100.0
Auraiya	37.9	0.0	0.0	100.0	0.0	100.0
Azamgarh	49.0	0.0	0.0	100.0	0.0	100.0
Baghpat	0.0	0.0	0.0	0.0	0.0	0.0
Bahraich	46.6	0.0	0.0	100.0	0.0	100.0
Ballia	27.3	0.0	0.0	100.0	0.0	100.0
Balrampur	24.1	0.0	0.0	0.0	0.0	100.0
Banda	22.6	0.0	0.0	0.0	0.0	100.0
Barabanki	27.8	0.0	0.0	100.0	0.0	100.0
Bareilly	25.6	0.0	0.0	100.0	0.0	100.0
Basti	36.0	0.0	0.0	100.0	0.0	100.0
Bijnor	13.9	0.0	0.0	0.0	0.0	100.0
Budaun	30.8	0.0	0.0	100.0	0.0	100.0
Bulandshahar	18.4	0.0	0.0	0.0	0.0	100.0
Chandauli	20.5	0.0	0.0	0.0	0.0	100.0
Chitrakoot	34.7	0.0	0.0	100.0	0.0	100.0
Deoria	12.1	0.0	0.0	0.0	0.0	100.0
Etah	48.7	0.0	0.0	100.0	0.0	100.0
Etawah	29.6	0.0	0.0	100.0	0.0	100.0
Faizabad	34.4	0.0	0.0	100.0	0.0	100.0
Farrukhabad	35.7	0.0	0.0	100.0	0.0	100.0
Fatehpur	33.8	0.0	0.0	100.0	0.0	100.0
Firozabad	33.7	0.0	0.0	100.0	0.0	100.0
Gautam Buddha Nagar	16.3	0.0	0.0	0.0	0.0	100.0
Ghaziabad	1.4	0.0	0.0	0.0	0.0	100.0
Ghazipur	9.4	0.0	0.0	0.0	0.0	100.0
Gonda	53.0	0.0	100.0	100.0	0.0	100.0
Gorakhpur	18.3	0.0	0.0	0.0	0.0	100.0
Hamirpur	28.0	0.0	0.0	100.0	0.0	100.0
Hardoi	40.7	0.0	0.0	100.0	0.0	100.0
Hathras	17.4	0.0	0.0	0.0	0.0	100.0

Table A5: Summary statistics on the implementation of RGGVY, by district.

Summary Statistic: RGGVY by District (Part B)

	Mean	25th pctl	50th pctl	75th pctl	Min	Max
Jalaun	11.4	0.0	0.0	0.0	0.0	100.0
Jaunpur	21.1	0.0	0.0	0.0	0.0	100.0
Jhansi	24.5	0.0	0.0	0.0	0.0	100.0
Jyotiba Phule Nagar	53.5	0.0	100.0	100.0	0.0	100.0
Kannauj	35.6	0.0	0.0	100.0	0.0	100.0
Kanpur Dehat	34.6	0.0	0.0	100.0	0.0	100.0
Kanpur Nagar	17.4	0.0	0.0	0.0	0.0	100.0
Kaushambi	25.6	0.0	0.0	100.0	0.0	100.0
Kheri	36.9	0.0	0.0	100.0	0.0	100.0
Kushinagar	28.0	0.0	0.0	100.0	0.0	100.0
Lalitpur	37.3	0.0	0.0	100.0	0.0	100.0
Lucknow	4.0	0.0	0.0	0.0	0.0	100.0
Mahoba	42.3	0.0	0.0	100.0	0.0	100.0
Mahrajganj	24.6	0.0	0.0	0.0	0.0	100.0
Mainpuri	33.8	0.0	0.0	100.0	0.0	100.0
Mathura	4.1	0.0	0.0	0.0	0.0	100.0
Mau	45.1	0.0	0.0	100.0	0.0	100.0
Meerut	0.0	0.0	0.0	0.0	0.0	0.0
Mirzapur	32.3	0.0	0.0	100.0	0.0	100.0
Moradabad	20.7	0.0	0.0	0.0	0.0	100.0
Muzaffarnagar	0.0	0.0	0.0	0.0	0.0	0.0
Pilibhit	34.2	0.0	0.0	100.0	0.0	100.0
Pratapgarh	19.4	0.0	0.0	0.0	0.0	100.0
Rae Bareli	97.2	100.0	100.0	100.0	0.0	100.0
Rampur	33.5	0.0	0.0	100.0	0.0	100.0
Saharanpur	0.0	0.0	0.0	0.0	0.0	0.0
Sant Kabir Nagar	36.9	0.0	0.0	100.0	0.0	100.0
Sant Ravidas Nagar Bhadohi	12.4	0.0	0.0	0.0	0.0	100.0
Shahjahanpur	35.8	0.0	0.0	100.0	0.0	100.0
Shrawasti	46.3	0.0	0.0	100.0	0.0	100.0
Siddharthnagar	45.2	0.0	0.0	100.0	0.0	100.0
Sitapur	39.6	0.0	0.0	100.0	0.0	100.0
Sonbhadra	24.6	0.0	0.0	0.0	0.0	100.0
Sultanpur	90.0	100.0	100.0	100.0	0.0	100.0
Unnao	36.6	0.0	0.0	100.0	0.0	100.0
Varanasi	0.0	0.0	0.0	0.0	0.0	0.0
Total	31.1	0.0	0.0	100.0	0.0	100.0

Table A6: Summary statistics on the implementation of RGGVY, by district.

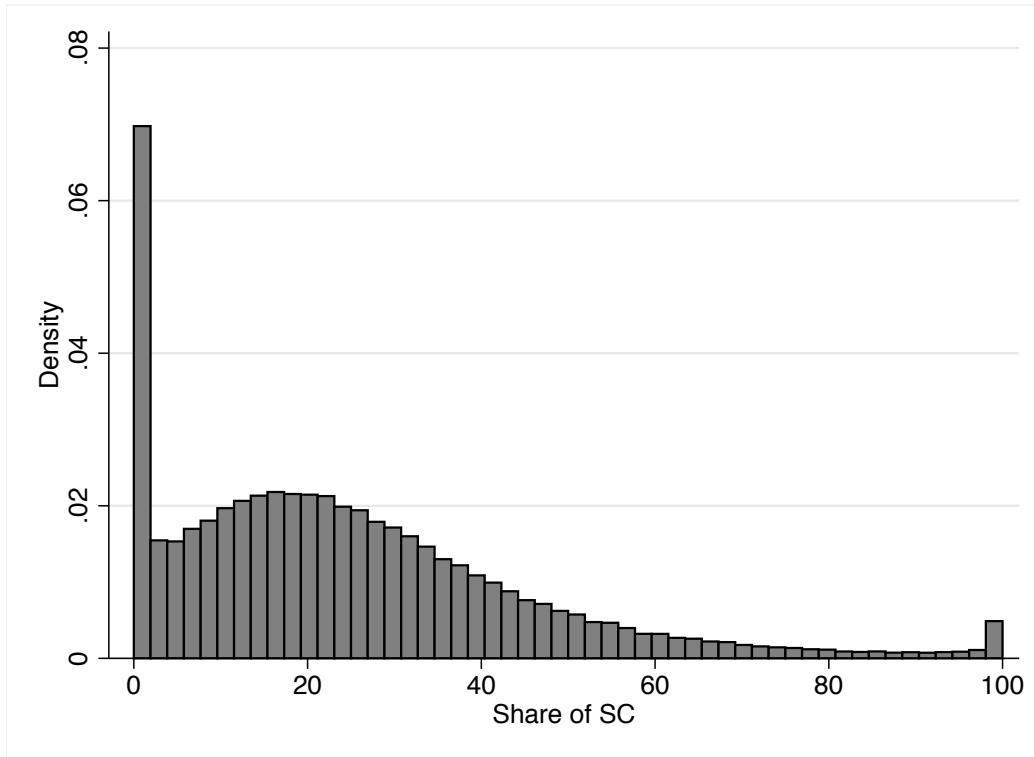


Figure A3: Distribution of the share of scheduled caste members per village (entire sample).

Figure A3 demonstrates that there is considerable variation across villages in SC population. The x -axis shows the SC population percentage on a 0-100 scale, and the y -axis shows the density of different percentages. While a large number of villages have no SC population at all and there are also villages with only SC people, the vast majority of the villages fall on a right-skewed normal distribution. The average SC percentage in our dataset is 24.6%.

A2 Pre-RGGVY Rural Electrification

In conducting our study, we consider the relationship between village electrification and SC population *before* the RGGVY begins. To achieve this goal, we use the 2001 Census of India. While this earlier census unfortunately does not contain information about household electrification, it does allow us to compute SC population percentages and assess village electrification. Table A7 regresses the electrification status in 2001 on the village SC population percentage. The SC percentage is actually *positively* correlated with the likelihood of village electrification. Increasing the

SC percentage by 10 points, for example, increases the probability of village electrification by approximately 1 percentage point across the models – an association that is sensitive neither to the inclusion of fixed effects nor to that of control variables.

If the Dalit population is generally underprivileged in India and Uttar Pradesh, why would their villages enjoy higher levels of electrification before the RGGVY? To understand the initially puzzling relationship between SC population percentage and village electrification, Table A8 offers summary statistics by the decile of SC population percentage. As the table shows, the surprising result is almost entirely driven by villages with no Dalits at all: the difference between the 2nd and 10th decile in the probability of village electrification is only 6 percentage points, while the difference between the 1st and 2nd decile alone is 7 percentage points. Because villages without Dalits tend to be very small (average population: 429), it is unsurprising that they have no village electrification. Villages in all other deciles are larger, so they have higher probabilities of village electrification and road construction, but their development outcomes (no assets, literacy) are not very different.

- Table A7 regresses the electrification status in 2001 on the village SC population percentage. The dependent variable in all models is electrification status in 2001, which is 100 if the village is electrified and zero otherwise. Models 2-6 include constituency fixed effects, and standard errors are clustered by constituency throughout.
- Table A8 offers summary statistics by the decile of SC population percentage.

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	0.11*** (0.02)	0.10*** (0.01)	0.10*** (0.01)	0.10*** (0.01)	0.10*** (0.01)	0.10*** (0.01)
Distance (log)			-0.98*** (0.21)			-0.90*** (0.21)
Population (log)				4.07*** (0.31)		3.92*** (0.32)
Pucca Road					3.20*** (0.48)	1.32*** (0.47)
Constant	33.15*** (0.77)					
Constituency FE		✓	✓	✓	✓	✓
Observations	96557	96557	90683	96557	96196	90454
R^2	0.00	0.00	0.00	0.01	0.00	0.01
# Clusters	402	402	401	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Dependent variable: electrification status in 2001 (= 100 if electrified; 0 otherwise). All models estimated with constituency fixed effects. The standard errors are clustered by constituency.

Decile	Share of SC (cutoff)	Dom. Electricity (2001)	Population	Road	No assets	Literacy	Distance to nearest town
1st	0%	26.4%	429	50.3%	9.1%	57%	15.6
2nd	6.2%	33.2%	1460	64.2%	11.2%	53.8%	16.3
3rd	11.6%	35.5%	1947	67.0%	10.8%	54.6%	17.1
4th	16.3%	36.7%	2121	68.3%	10.6%	55.5%	17.6
5th	21.0%	37.0%	2080	69.3%	10.4%	56.4%	17.3
6th	25.8%	36.4%	2011	70.0%	10.6%	56.6%	17.4
7th	31.5%	37.1%	1914	69.5%	10.5%	57.1%	17.5
8th	38.9%	38.4%	1715	70.2%	10.9%	56.9%	17.6
9th	51.3%	38.8%	1450	68.8%	11.3%	56.2%	17.8
10th	Above 51.3%	39.2%	976	66.8%	14.0%	53.2%	17.6

Table A8: Dependent variable: village electrification rate/probability (%) in 2001 by decile of SC population percentage in a given village. The second decile is somewhat smaller than the others because villages with zero percent SC are excluded from this group.

A3 Regression Discontinuity: Identifying Assumptions

In an RDD analysis, local average treatment effects are identified by quantifying a discontinuous jump in the outcome at the threshold (Imbens and Lemieux, 2008). In our case, this means comparing RGGVY implementation between electoral constituencies that were barely won or lost by the BSP. The basic identifying assumption is that while the outcome may be related to the forcing variable, such as the margin of victory, the sharp discontinuity at the cut-off – in our case, BSP victory – allows the estimation of local average treatment effects for villages within electoral constituencies in which the BSP barely won or lost.

The identifying assumption can be tested in several ways. The first is to compare pre-treatment covariate values in constituencies barely won or lost by the BSP. These balance statistics are provided in Table A12 to A14. As the table shows, the treatment (BSP victory by a narrow margin) and control (BSP loss by a narrow margin) are statistically indistinguishable for pre-treatment covariates.

Following McCrary (2008), we also examine any discontinuities at the cut-off (Figure A6). The test shows that there is no suspicious discontinuity, alleviating concerns about electoral fraud and other irregularities in the conduct of election.

To scrutinize the external validity of the results, we also replicate them in the full sample. While the full sample estimation does not admit causal inference, it can be used to see whether the correlations in the data are broadly consistent with the results from the close elections. If they are consistent, this observation alleviates concerns about close elections being a special case without external validity.

A4 Regression Discontinuity: Summary Statistics

- Figure A4 shows the margin of victory for each constituency-election in the RDD sample (5% margin of victory).
- Table A9 summarizes the RDD sample. The upper panel summarizes the data at the village level; the lower panel summarizes the data at the constituency-election level. In total, we

have 235 close constituency-elections when the sample is restricted to a 5% margin of victory.

- Table A10 compares BSP and non-BSP MLAs. As the table shows, both the candidate and constituency characteristics are mostly similar. The only exception – an unsurprising one – is that BSP MLAs tend to come from SC-reserved constituencies.
- Figure A5 shows the kernel density function for the SC share in the RDD sample.
- Table A5 is the histogram of BSP wins and losses (i.e. when it came second) based on a ± 5 percent margin.
- Table A11 reports the summary statistics for the main variables used for the regression discontinuity analysis (using a ± 5 percent margin).

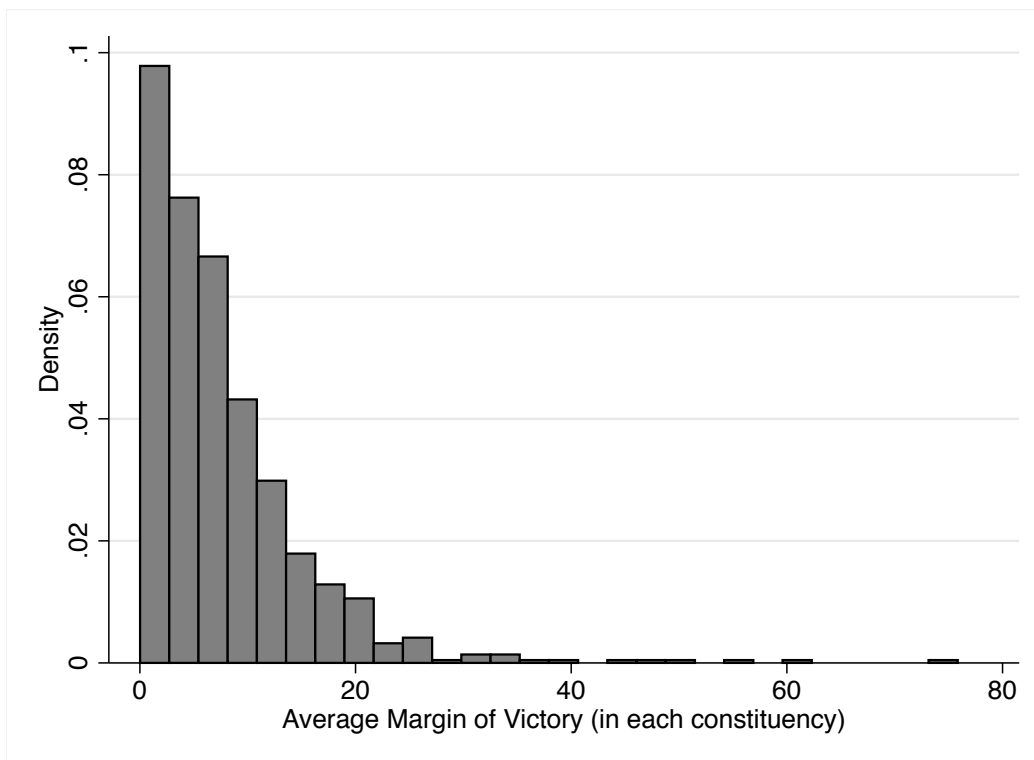


Figure A4: Distribution of the margin of victory for the winning party against the first runner-up in each constituency-election.

<i>Category</i>	Village Level		<i>Total # of villages</i>
	<i>Won by BSP</i>	<i>Lost by BSP</i>	
All village-elections	77,617	115,497	193,114
All village-elections, BSP top-2	77,617	53,723	131,340
All villages, 2002, BSP top-2	25,556	27,277	52,833
All villages, 2007, BSP top-2	52,061	26,446	78,507
Village-elections, BSP top-2, 1% win/loss margin	7,170	6,916	14,086
Village-elections, BSP top-2, 2% win/loss margin	14,266	12,527	26,793
Village-elections, BSP top-2, 5% win/loss margin	34,281	27,798	62,079

<i>Category</i>	Constituency Level		<i>Total # of constituencies</i>
	<i>Won by BSP</i>	<i>Lost by BSP</i>	
All constituency-elections	303	501	804
All constituency-elections, BSP top-2	303	217	520
All constituencies, 2002, BSP top-2	98	108	206
All constituencies, 2007, BSP top-2	205	109	314
Constituency-elections, BSP top-2, 1% win/loss margin	27	29	56
Constituency-elections, BSP top-2, 2% win/loss margin	51	50	101
Constituency-elections, BSP top-2, 5% win/loss margin	129	106	235

Table A9: Summary of the RDD sample.

	Full Sample		5% Sample	
	Non-BSP	BSP	Non-BSP	BSP
Candidate Characteristics				
Male	0.934	0.951	0.96	0.974
Higher Education	0.67	0.568	0.65	0.623
Number of Criminal Charges	1.107	1.01	1.25	0.961
Asset (10,000 rupees)	1,448.601	832.718	1,094.880	649.169
Debt (10,000 rupees)	100.952	136.879	76.930	87.660
Constituency Characteristics				
SC Constituency	0.142	0.301	0.11	0.208
Domestic Electricity (2001)	0.342	0.32	0.318	0.308
Household Electrification Rate (2011)	0.267	0.248	0.256	0.229
Literacy Rate (2001)	0.558	0.563	0.556	0.56
Literacy Rate (2011)	0.424	0.432	0.421	0.429
Number of Electors (10,000 people)	28.422	27.941	28.502	28.258
Num. Obs.	197	206	100	77

Table A10: Comparison between BSP and non-BSP MLAs.

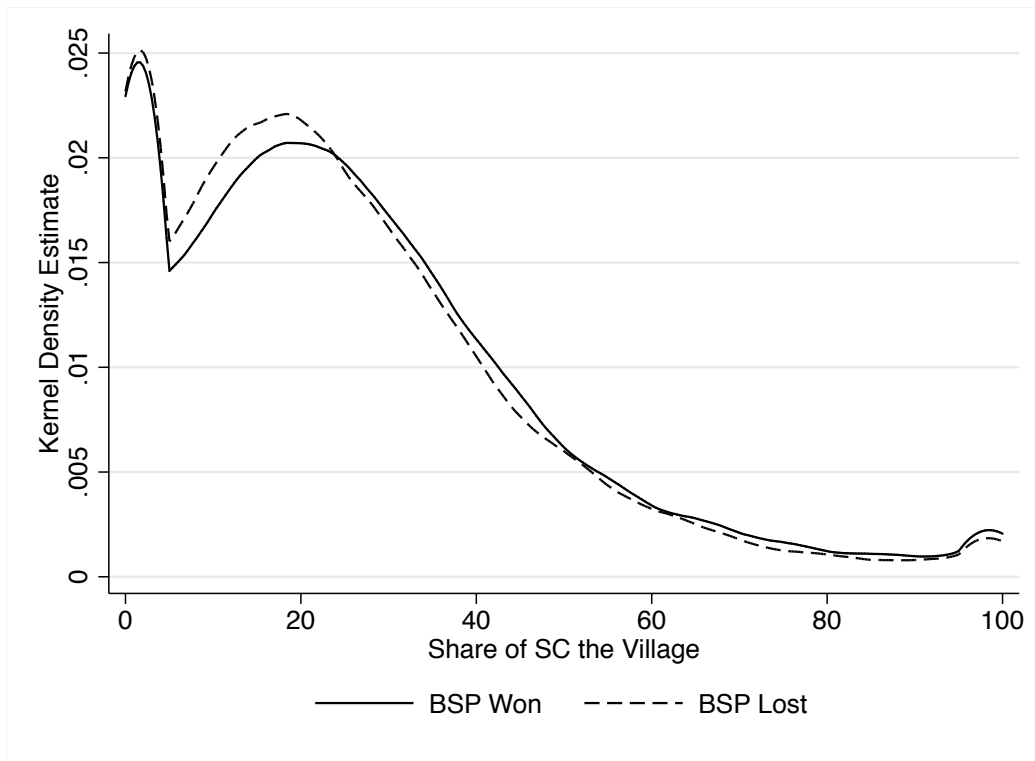


Figure A5: Histogram (kernel density function) of the share of SC in the sample, split by cases where BSP won and BSP came second, when the margin of victory is ± 5 percent.

Summary Statistic					
	Mean	S.D.	Min.	Max	Obs.
RGGVY	30.40	46.00	0	100	62079
Domestic Electricity (2001)	34.82	47.64	0	100	62079
Lighting Source: Electricity	21.84	23.10	0	100	62079
Share SC (%)	25.30	21.22	0	100	62079
BSP Margin	0.27	2.77	-5	5	62079
BSP Win	0.55	0.50	0	1	62079
Population (log)	6.85	1.11	1	11	62079
Distance (log)	2.44	1.09	0	5	58571
Pucca Road	0.64	0.48	0	1	61800
Lack of Asset	10.84	10.22	0	100	62079
Literacy Rate (%)	56.11	11.09	0	100	62079

Table A11: Summary statistics for the sample used in the RDD study (observations with a margin below 5%). The unit of analysis is village-election.

A5 Regression Discontinuity: Balance Statistics and Density Tests

- Tables A12-A14 show the balance statistics for the 1%, 2%, and 5% RDD samples.
- Figure A6 shows the results of a McCrary (2008) density test.

	BSP=0			BSP=1			P-value of Difference
	Mean	S.D.	Obs.	Mean	S.D.	Obs.	
Margin of Victory	0.49	0.29	29	0.46	0.26	27	0.67
Total Scheduled Castes Population of Village	416.01	153.25	29	375.72	134.61	27	0.30
Total Scheduled Tribes Population of Village	6.60	18.14	29	4.89	11.42	27	0.68
Total Population of Village	1718.45	596.54	29	1633.89	465.20	27	0.57
Area of Village (hectares)	253.77	165.12	29	186.54	89.90	27	0.07
Number of Co-operative Commercial Bank Credit Societies (Y/N)	0.02	0.01	29	0.02	0.02	27	0.95
Paved Road	0.07	0.04	29	0.09	0.04	27	0.15
Distance from the Nearest Town (km)	0.59	0.13	29	0.60	0.13	27	0.77
Power Supply (A/NA)	11.10	3.56	29	8.76	1.94	27	<0.01**
Domestic Electricity (2001)	0.68	0.17	29	0.75	0.18	27	0.18
Agricultural Electricity (2001)	0.36	0.13	29	0.31	0.12	27	0.10
Electricity (other purposes) (2001)	0.23	0.13	29	0.23	0.12	27	0.91
Electricity (all purposes) (2001)	0.02	0.02	29	0.02	0.02	27	0.21
Total Irrigated Area	0.25	0.19	29	0.37	0.23	27	0.05**
Unirrigated Area	186.39	147.11	29	206.10	474.68	27	0.83
	88.30	136.55	29	41.85	53.19	27	0.10

Table A12: Balance statistic at the constituency-election level. Village-elections where the winning margin was below 1 percent, and where neither of the top-2 candidates were members of BSP, were dropped. The summary statistics of each variable were then computed by constituency-election. The p-value is based on a *t* test where the null hypothesis that the means are equal. *= $p < 0.05$, **= $p < 0.01$.

	BSP=0			BSP=1			P-value of Difference
	Mean	S.D.	Obs.	Mean	S.D.	Obs.	
Margin of Victory	0.94	0.61	50	0.95	0.60	51	0.96
Total Scheduled Castes Population of Village	415.83	163.59	50	407.57	170.79	51	0.80
Total Scheduled Tribes Population of Village	7.74	17.80	50	3.24	8.51	51	0.11
Total Population of Village	1773.85	670.28	50	1697.81	688.36	51	0.58
Area of Village (hectares)	248.56	167.96	50	222.03	164.19	51	0.42
Number of Co-operative Commercial Bank Credit Societies (Y/N)	0.02	0.02	50	0.02	0.02	51	0.76
Paved Road	0.07	0.04	50	0.08	0.04	51	0.22
Distance from the Nearest Town (km)	0.60	0.15	50	0.62	0.15	51	0.46
Power Supply (A/NA)	10.37	3.52	50	9.30	2.08	51	0.07
Domestic Electricity (2001)	0.68	0.18	50	0.75	0.18	51	0.07
Agricultural Electricity (2001)	0.37	0.14	50	0.32	0.12	51	0.05*
Electricity (other purposes) (2001)	0.21	0.13	50	0.23	0.10	51	0.48
Electricity (all purposes) (2001)	0.02	0.02	50	0.02	0.02	51	0.57
Total Irrigated Area	0.25	0.18	50	0.36	0.23	51	0.01**
Unirrigated Area	158.13	122.51	50	171.55	348.69	51	0.80
	68.78	112.23	50	51.43	86.38	51	0.39

Table A13: Balance statistic at the constituency-election level. Village-elections where the winning margin was below 2 percent, and where neither of the top-2 candidates were members of BSP, were dropped. The summary statistics of each variable were then computed by constituency-election. The p-value is based on a *t* test where the null hypothesis that the means are equal. *= $p < 0.05$, **= $p < 0.01$.

	BSP=0			BSP=1			P-value of Difference
	Mean	S.D.	Obs.	Mean	S.D.	Obs.	
Margin of Victory	2.26	1.50	106	2.41	1.41	129	0.44
Total Scheduled Castes Population of Village	399.95	167.34	106	416.86	176.11	129	0.45
Total Scheduled Tribes Population of Village	6.86	16.02	106	13.46	79.49	129	0.40
Total Population of Village	1784.53	632.58	106	1744.80	725.18	129	0.66
Area of Village (hectares)	236.47	146.58	106	246.75	197.21	129	0.66
Number of Co-operative Commercial Bank Credit Societies (Y/N)	0.02	0.02	106	0.02	0.01	129	0.52
Paved Road	0.08	0.04	106	0.08	0.04	129	0.84
Distance from the Nearest Town (km)	0.61	0.15	106	0.60	0.13	129	0.75
Power Supply (A/NA)	9.95	3.58	106	9.75	2.81	129	0.63
Domestic Electricity (2001)	0.71	0.18	106	0.71	0.18	129	0.93
Agricultural Electricity (2001)	0.37	0.14	106	0.34	0.12	129	0.15
Electricity (other purposes) (2001)	0.23	0.13	106	0.25	0.13	129	0.33
Electricity (all purposes) (2001)	0.02	0.02	106	0.02	0.02	129	0.33
Total Irrigated Area	0.29	0.20	106	0.30	0.20	129	0.58
Unirrigated Area	176.48	264.17	106	151.78	239.28	129	0.45
	69.04	162.54	106	67.29	178.48	129	0.93

Table A14: Balance statistic at the constituency-election level. Village-elections where the winning margin was below 5 percent, and where neither of the top-2 candidates were members of BSP, were dropped. The summary statistics of each variable were then computed by constituency-election. The p-value is based on a *t* test where the null hypothesis that the means are equal. *= $p < 0.05$, **= $p < 0.01$.

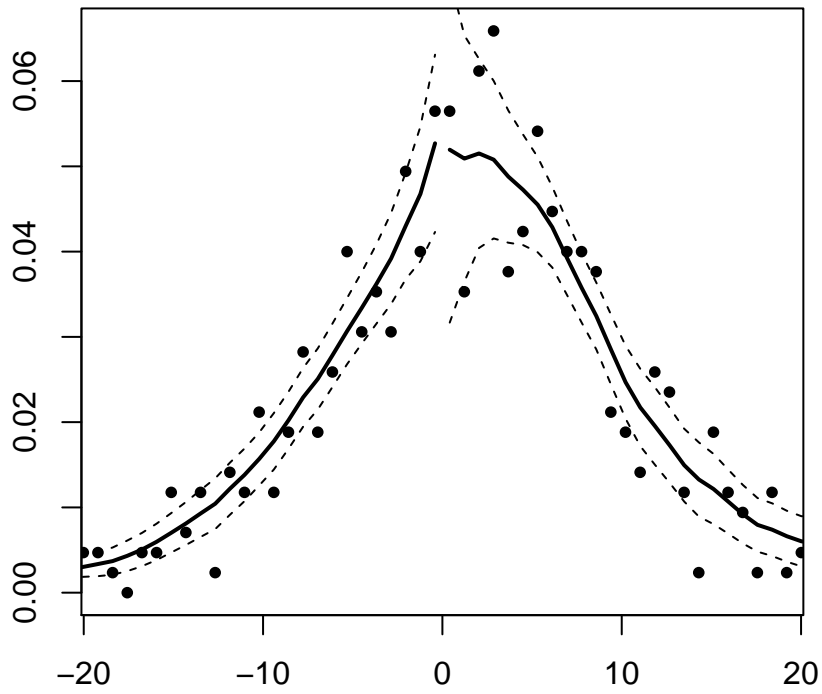


Figure A6: McCrary (2008) density test shows that there is no suspicious discontinuity in the treatment assignment around the cutoff. The p -value for rejecting the null hypothesis is 0.77.

A6 Regression Discontinuity: Additional Analysis

- In Table A15, we estimate the correlation between a BSP victory and RGGVY implementation in the full sample.
- Table A16 reports the estimates of the RDD analysis, limiting the sample to 2002.
- Table A17 reports the estimates of the RDD analysis, limiting the sample to 2007.
- Table A18 reports the estimates of the RDD analysis, but adds an interaction effect between the treatment (a BSP win) and the share of SC in the village. The sample is limited to 2002.
- Table A19 reports the estimates of the RDD analysis, but adds an interaction effect between the treatment (a BSP win) and the share of SC in the village. The sample is limited to 2007.
- Figures A7-A9 reports the regression discontinuity graph. Unlike traditional RDD figures, we bin observations to account for the dichotomous nature of the dependent variable (RGGVY).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BSP Win	-3.06*	-3.32*	-0.53	-0.47	-2.07	-2.29	0.02	0.04
	(1.78)	(1.93)	(3.13)	(3.13)	(1.93)	(2.08)	(3.40)	(3.39)
2007 Election		0.91*	0.72	0.72		0.74	0.46	0.47
		(0.54)	(1.15)	(1.15)		(0.54)	(1.15)	(1.14)
BSP Margin			-0.09	-0.04			-0.05	-0.02
			(0.19)	(0.26)			(0.19)	(0.25)
BSP Win * Margin				-0.10				-0.08
				(0.32)				(0.32)
BSP Win * Share SC					-0.02	-0.02	-0.02	-0.02
					(0.03)	(0.03)	(0.03)	(0.03)
Share SC (%)					-0.16***	-0.16***	-0.16***	-0.16***
					(0.03)	(0.03)	(0.03)	(0.03)
Constant	32.31***	31.96***	29.88***	30.18***	36.15***	35.86***	34.08***	34.32***
	(1.52)	(1.40)	(2.20)	(2.42)	(1.59)	(1.49)	(2.48)	(2.74)
Observations	193114	193114	131340	131340	193114	193114	131340	131340
R ²	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
# Clusters	402	402	340	340	402	402	340	340

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Full sample, mimicking both the RDD and the RDD with interactions. Dependent variable: RGGVY (if present, RGGVY= 100). The standard errors are clustered by constituency.

	Margin<1%			Margin<2%			Margin<5%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BSP Win	6.16 (6.98)	29.42** (13.70)	32.68** (14.20)	0.92 (7.35)	13.57 (10.27)	14.04 (10.24)	0.35 (4.90)	1.93 (8.57)	2.06 (8.43)
BSP Margin		-27.36** (11.21)	-11.59 (6.88)		-8.07 (6.24)	-3.98 (8.31)		-0.33 (1.64)	0.99 (2.14)
BSP Win * Margin			-37.24 (23.83)			-8.85 (11.76)			-2.78 (3.19)
Constant	27.70*** (2.62)	16.69*** (5.25)	23.04*** (3.28)	32.06*** (5.64)	25.70*** (4.92)	28.93*** (4.69)	30.01*** (3.74)	29.20*** (5.04)	32.47*** (5.84)
Observations	6967	6967	6967	10914	10914	10914	26051	26051	26051
R ²	0.00	0.03	0.04	0.00	0.01	0.01	0.00	0.00	0.00
# Clusters	29	29	29	45	45	45	99	99	99

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A16: Dependent variable: RGGVY (= 100). Standard errors clustered by constituency. The sample is limited to 2002.

	Margin<1%			Margin<2%			Margin<5%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BSP Win	0.01 (7.02)	-19.20 (15.03)	-19.09 (14.73)	-5.59 (5.75)	3.37 (10.26)	3.49 (10.37)	-1.81 (3.69)	0.92 (6.92)	0.83 (6.90)
BSP Margin		20.77 (13.08)	18.69 (13.79)		-4.11 (4.59)	-3.36 (6.57)		-0.59 (1.24)	-0.36 (2.04)
BSP Win * Margin			3.68 (24.59)			-1.60 (9.17)			-0.40 (2.55)
Constant	30.06*** (3.87)	39.03*** (6.98)	38.13*** (7.77)	32.76*** (3.96)	28.34*** (5.01)	29.15*** (6.11)	31.60*** (2.90)	30.29*** (3.55)	30.80*** (4.58)
Observations	7119	7119	7119	15879	15879	15879	36028	36028	36028
R ²	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00
# Clusters	27	27	27	56	56	56	136	136	136

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: Dependent variable: RGGVY (= 100). Standard errors clustered by constituency. The sample is limited to 2007.

	Margin < 1%			Margin < 2%			Margin < 5%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BSP Win	4.39 (7.74)	29.87* (15.03)	32.94** (14.98)	0.69 (8.02)	13.82 (10.81)	13.76 (10.39)	0.23 (5.75)	1.46 (8.77)	1.38 (8.58)
BSP Win * Share SC/ST	0.06 (0.11)	-0.03 (0.10)	-0.02 (0.11)	0.01 (0.10)	-0.03 (0.09)	-0.01 (0.09)	0.01 (0.07)	0.01 (0.06)	0.02 (0.07)
Share SC/ST (%)	-0.19** (0.08)	-0.13 (0.08)	-0.17* (0.08)	-0.20*** (0.07)	-0.17** (0.07)	-0.19*** (0.07)	-0.15*** (0.05)	-0.15*** (0.05)	-0.16*** (0.05)
BSP Margin		-27.07** (11.64)	-9.68 (7.59)		-7.65 (6.28)	-2.82 (8.33)		-0.25 (1.65)	1.15 (2.14)
BSP Win * Margin			-40.69 (24.21)			-10.28 (11.70)			-2.93 (3.21)
Constant	33.17*** (4.14)	20.62*** (7.40)	28.68*** (5.65)	37.58*** (6.55)	30.57*** (5.92)	34.99*** (5.57)	34.02*** (4.44)	33.37*** (5.52)	37.02*** (6.12)
Observations	6967	6967	6967	10914	10914	10914	26051	26051	26051
R ²	0.01	0.04	0.05	0.01	0.02	0.02	0.00	0.01	0.01
# Clusters	29	29	29	45	45	45	99	99	99

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A18: Dependent variable: RGGVY (= 100). The treatment (a BSP win) is interacted with the share of SC in the village. Standard errors clustered by constituency. The sample is limited to 2002.

	Margin < 1%			Margin < 2%			Margin < 5%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BSP Win	0.44 (7.88)	-17.61 (15.21)	-17.57 (15.10)	-7.87 (6.85)	-0.39 (10.05)	-0.36 (10.09)	-0.63 (4.52)	1.43 (7.31)	1.23 (7.27)
BSP Win * Share SC/ST	-0.08 (0.09)	-0.07 (0.10)	-0.07 (0.10)	0.09 (0.08)	0.10 (0.08)	0.10 (0.08)	-0.03 (0.06)	-0.03 (0.06)	-0.03 (0.06)
Share SC/ST (%)	-0.30*** (0.08)	-0.30*** (0.08)	-0.30*** (0.08)	-0.33*** (0.06)	-0.33*** (0.06)	-0.33*** (0.06)	-0.23*** (0.05)	-0.23*** (0.05)	-0.23*** (0.05)
BSP Margin		19.32 (12.93)	17.67 (14.36)		-3.50 (4.53)	-2.99 (6.47)		-0.43 (1.22)	-0.08 (2.03)
BSP Win * Margin			2.93 (24.52)			-1.09 (9.05)			-0.62 (2.53)
Constant	37.66*** (5.06)	45.79*** (7.27)	45.10*** (8.04)	40.80*** (4.97)	36.93*** (5.47)	37.50*** (6.22)	36.98*** (3.57)	35.96*** (4.05)	36.80*** (4.94)
Observations	7119	7119	7119	15879	15879	15879	36028	36028	36028
R ²	0.02	0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.01
# Clusters	27	27	27	56	56	56	136	136	136

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A19: Dependent variable: RGGVY (= 100). The treatment (a BSP win) is interacted with the share of SC in the village. Standard errors clustered by constituency. The sample is limited to 2007.

	Margin < 3%				Margin < 4%			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BSP Win	-0.50 (3.87)	-0.46 (3.85)	3.00 (6.11)	2.96 (6.11)	-1.28 (3.45)	-1.28 (3.45)	3.09 (5.70)	2.96 (5.68)
2007 Election		-0.95 (3.33)	-0.86 (3.30)	-0.58 (3.27)		0.19 (2.78)	0.16 (2.77)	0.26 (2.74)
BSP Margin			-1.18 (1.88)	-0.25 (2.74)			-1.16 (1.31)	-0.61 (1.99)
BSP Win * Margin				-1.83 (3.75)				-1.01 (2.59)
Constant	31.26*** (2.93)	31.82*** (3.85)	30.05*** (3.90)	31.23*** (4.23)	31.64*** (2.70)	31.52*** (3.40)	29.43*** (3.69)	30.38*** (4.22)
Observations	40121	40121	40121	40121	50797	50797	50797	50797
R ²	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
# Clusters	142	142	142	142	174	174	174	174

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A20: Dependent variable: RGGVY (= 100). The treatment (a BSP win) is interacted with the share of SC in the village. Standard errors clustered by constituency. Different set of bandwidths.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SC Win	1.05 (2.63)	1.05 (2.63)	-1.94 (3.00)	-2.22 (3.11)	2.09 (3.22)	2.09 (3.22)	-0.87 (3.60)	-1.27 (3.78)
2007 Election		-0.17 (0.57)	-0.31 (0.61)	-0.31 (0.62)		-0.14 (0.57)	-0.28 (0.61)	-0.27 (0.62)
SC Margin		0.21* (0.12)	0.21* (0.12)	0.20 (0.13)			0.21* (0.12)	0.19 (0.13)
SC Win * Margin				0.07 (0.27)				0.10 (0.27)
SC Win * Share SC					0.00 (0.05)	0.00 (0.05)	-0.00 (0.05)	-0.00 (0.05)
Share SC (%)					-0.19*** (0.02)	-0.19*** (0.02)	-0.19*** (0.02)	-0.19*** (0.02)
Constant	30.48*** (1.29)	30.57*** (1.36)	32.14*** (1.69)	32.04*** (1.77)	34.78*** (1.41)	34.85*** (1.48)	36.45*** (1.80)	36.30*** (1.88)
Observations	181791	181791	181791	181791	181791	181791	181791	181791
R ²	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
# Clusters	399	399	399	399	399	399	399	399

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A21: RDD analysis with SC victory effects (instead of BSP): 1%, 2%, 5% bandwidths. Dependent variable: RGGVY (if present, RGGVY= 100). The standard errors are clustered by constituency.

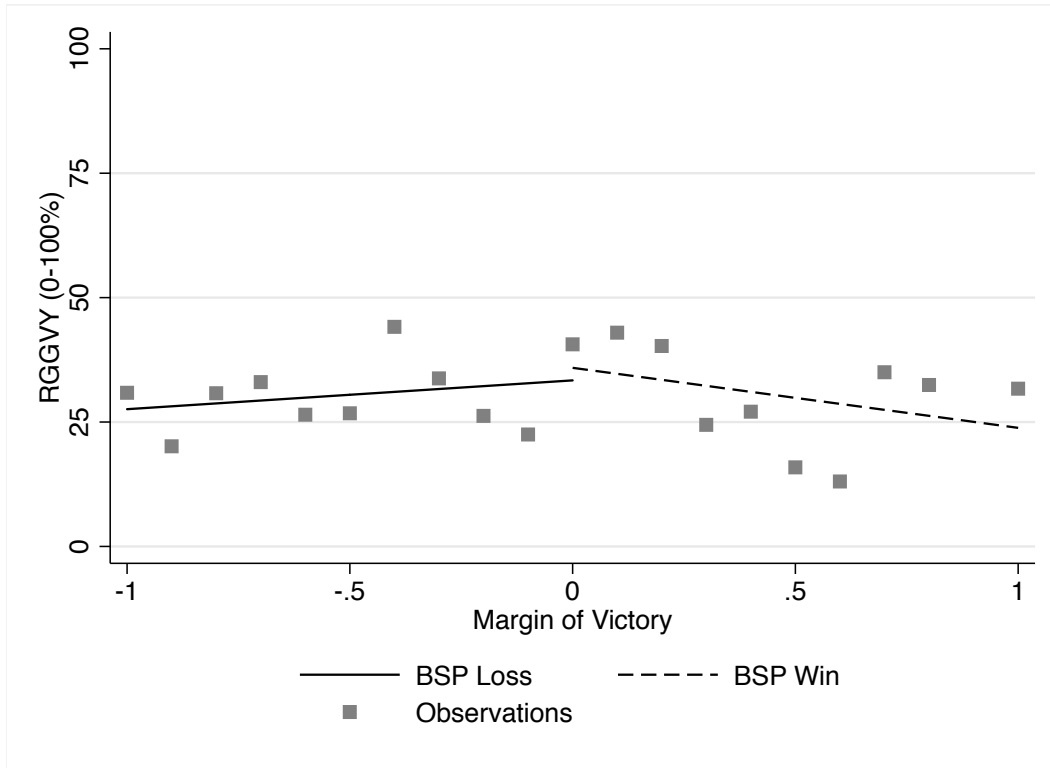


Figure A7: Regression discontinuity graph with a 1% margin. Observations are binned by slides of 0.1 (i.e. from -1 to -0.9, from -0.9 to -0.8, ..., from 0.9 to 1). Within each bin, we take the share of villages that have benefited from RGGVY. These are the observations plotted on the x- and y-axis, respectively. We then fit two linear regressions on either side of the cutoff.

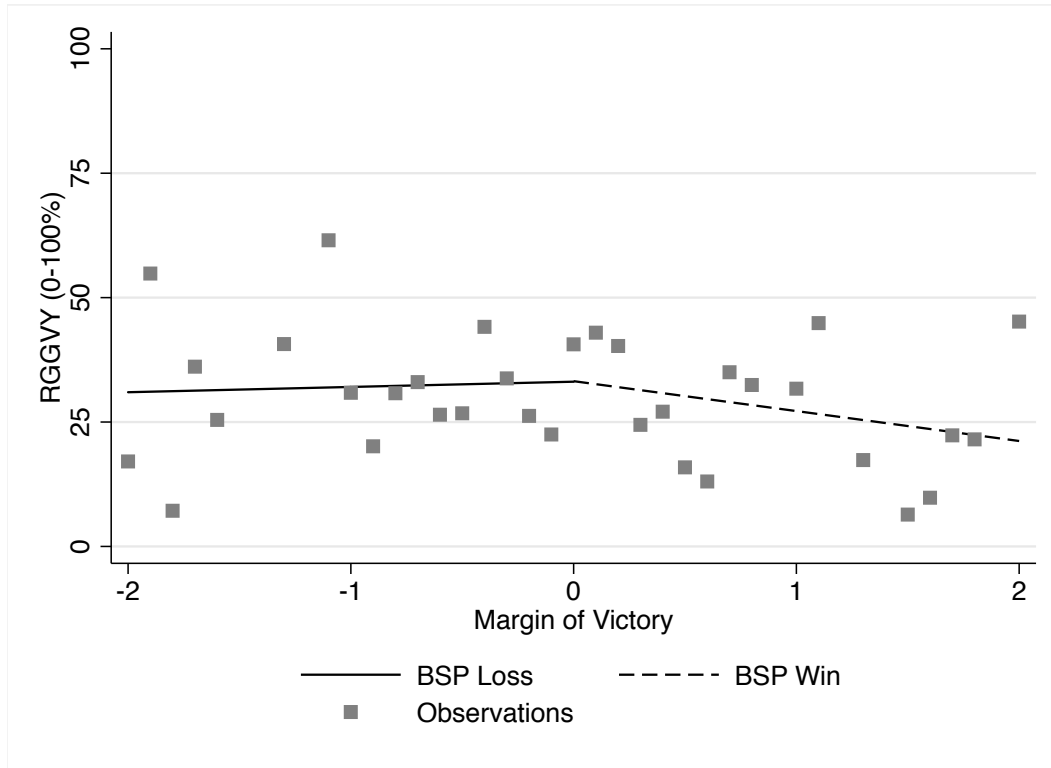


Figure A8: Regression discontinuity graph with a 2% margin. Observations are binned by slides of 0.1 (i.e. from -2 to -1.9, from -1.9 to -1.8, ..., from 1.9 to 2). Within each bin, we take the share of villages that have benefited from RGGVY. These are the observations plotted on the x- and y-axis, respectively. We then fit two linear regressions on either side of the cutoff.

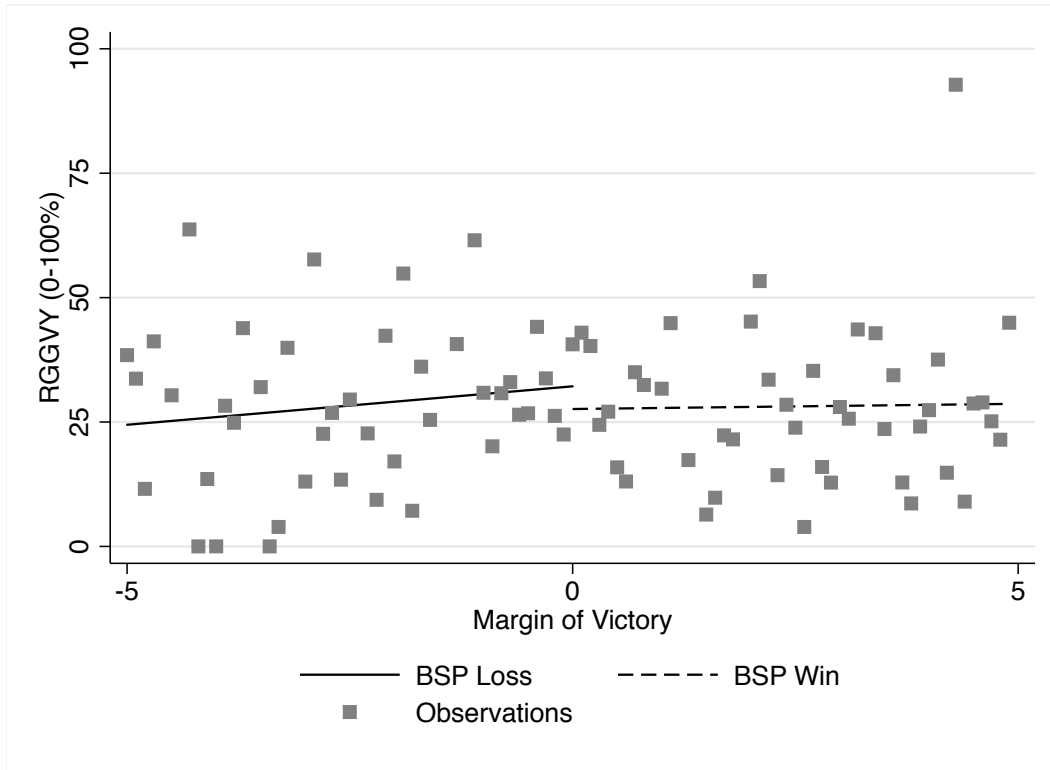


Figure A9: Regression discontinuity graph with a 5% margin. Observations are binned by slides of 0.1 (i.e. from -5 to -4.9, from -4.9 to -4.8, ..., from 4.9 to 5). Within each bin, we take the share of villages that have benefited from RGGVY. These are the observations plotted on the x- and y-axis, respectively. We then fit two linear regressions on either side of the cutoff.

A7 Regression Discontinuity: Conditioning on Reservation Status

- Table A22 conditions the effect of a BSP win on the constituency reservation status (SC versus general). The samples are based on the regression discontinuity thresholds.
- Table A23 conditions the effect of a BSP win on the constituency reservation status (SC versus general). All available observations are used to produce the estimates.
- Table A24 splits the analysis between reserved and non-reserved constituencies. As a result, the effect of a BSP win is interacted with the SC share in the village population, the margin of victory, and the reservation status.

	Margin<1%				Margin<2%				Margin<5%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
BSP Win	1.81 (5.86)	1.81 (5.86)	2.98 (12.40)	3.64 (13.49)	-6.72 (5.53)	-6.95 (5.59)	3.12 (8.15)	2.83 (8.10)	-1.77 (4.04)	-1.77 (4.04)	0.51 (5.86)
BSP Win * Share SC	-0.01 (0.09)	-0.01 (0.08)	-0.02 (0.08)	-0.01 (0.08)	0.03 (0.06)	0.03 (0.06)	0.02 (0.06)	0.03 (0.06)	-0.05 (0.05)	-0.05 (0.05)	-0.05 (0.05)
Share SC (%)	-0.25*** (0.05)	-0.25*** (0.05)	-0.25*** (0.05)	-0.26*** (0.05)	-0.25*** (0.04)	-0.26*** (0.04)	-0.25*** (0.04)	-0.25*** (0.04)	-0.18*** (0.04)	-0.18*** (0.04)	-0.18*** (0.04)
Reserved Constituency	2.63 (4.42)	2.63 (4.40)	2.48 (4.51)	2.93 (4.10)	-6.58 (5.29)	-7.93 (5.61)	-5.91 (5.97)	-6.76 (5.79)	-4.85 (5.58)	-5.02 (5.82)	-4.93 (5.94)
Reserved*BSP Win	17.97 (11.26)	17.97 (11.53)	17.72 (12.38)	15.98 (14.31)	16.48 (13.01)	17.70 (12.78)	16.32 (12.34)	17.59 (11.99)	11.74 (7.82)	11.87 (7.98)	12.06 (7.93)
2007 Election		0.00 (4.82)	-0.04 (4.98)	0.03 (4.95)		-4.31 (4.60)	-3.85 (4.52)	-3.02 (4.57)		-0.46 (2.56)	-0.36 (2.57)
BSP Margin			-1.28 (10.92)	2.69 (7.25)			-4.91 (3.67)	-1.99 (5.05)			-0.48 (0.96)
BSP Win * Margin				-8.43 (22.20)				-6.02 (7.23)			
Constant	34.71*** (4.26)	34.71*** (4.91)	34.22*** (5.91)	35.79*** (5.97)	40.67*** (4.49)	43.63*** (5.85)	37.87*** (6.09)	40.54*** (6.42)	36.41*** (3.21)	36.71*** (3.78)	35.46*** (4.39)
Observations	14086	14086	14086	14086	26793	26793	26793	26793	62079	62079	62079
R ²	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.01	0.01	0.01
# Clusters	55	55	55	55	97	97	97	97	200	200	200

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A22: Dependent variable: RGGVY (= 100). Standard errors clustered by constituency. Additional controls based on reservation status. Regression discontinuity framework.

	(1)	(2)	(3)	(4)
BSP Win	-1.21 (2.16)	-1.46 (2.25)	-0.15 (3.63)	-0.15 (3.62)
BSP Win * Share SC	-0.03 (0.03)	-0.03 (0.03)	-0.05 (0.03)	-0.05 (0.04)
Share SC (%)	-0.18*** (0.03)	-0.18*** (0.03)	-0.15*** (0.03)	-0.15*** (0.03)
Reserved Constituency	4.65 (4.15)	4.74 (4.16)	-2.50 (4.27)	-2.60 (4.32)
Reserved*BSP Win	-4.91 (4.99)	-5.07 (5.03)	2.30 (4.68)	2.50 (4.84)
Triple Interaction	0.06 (0.05)	0.06 (0.05)	0.06 (0.05)	0.06 (0.05)
2007 Election		0.90 (0.60)	0.30 (1.19)	0.30 (1.18)
BSP Margin			-0.06 (0.19)	-0.00 (0.26)
BSP Win * Margin				-0.12 (0.33)
Constant	35.46*** (1.73)	35.09*** (1.67)	34.54*** (2.75)	34.92*** (3.07)
Observations	193114	193114	131340	131340
R^2	0.01	0.01	0.01	0.01
# Clusters	402	402	340	340

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A23: Dependent variable: RGGVY (= 100). Standard errors clustered by constituency. Additional controls based on reservation status. The sample includes all available observations.

	Non-Reserved				Reserved			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BSP Win	-1.10 (2.16)	-1.22 (2.29)	-1.42 (3.77)	-0.99 (3.79)	-6.51 (4.32)	-7.65 (5.17)	6.89 (7.97)	10.99 (8.22)
BSP Win * Share SC	-0.03 (0.03)	-0.03 (0.03)	-0.04 (0.04)	-0.04 (0.04)	0.04 (0.06)	0.04 (0.06)	-0.01 (0.06)	-0.02 (0.06)
Share SC (%)	-0.17*** (0.03)	-0.17*** (0.03)	-0.16*** (0.03)	-0.16*** (0.03)	-0.19*** (0.06)	-0.19*** (0.06)	-0.13* (0.07)	-0.13* (0.07)
2007 Election		0.41 (0.48)	0.29 (1.30)	0.31 (1.28)		2.71 (2.24)	-0.11 (2.84)	-0.61 (2.82)
BSP Margin			0.03 (0.21)	0.18 (0.23)			-0.37 (0.45)	-1.77* (1.03)
BSP Win * Margin				-0.39 (0.33)				1.83* (1.10)
Constant	35.36*** (1.74)	35.19*** (1.64)	35.31*** (2.90)	36.35*** (2.96)	40.49*** (3.97)	39.62*** (3.61)	29.98*** (4.50)	22.97*** (6.36)
Observations	147718	147718	98356	98356	45396	45396	32984	32984
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
# Clusters	314	314	259	259	89	89	82	82

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A24: Dependent variable: RGGVY (= 100). Standard errors clustered by constituency. Sample split by reservation status.

A8 Regional Samples

- Tables A25-A28 show the main estimation results by region (West, Central, East, and Bundelkhand).

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.31*** (0.02)	-0.31*** (0.02)	-0.28*** (0.02)	-0.29*** (0.02)	-0.30*** (0.02)	-0.26*** (0.02)
Distance (log)		2.77*** (0.48)				2.37*** (0.44)
Domestic Electricity (2001)			-0.14*** (0.01)			-0.14*** (0.01)
Population (log)				-7.02*** (0.73)		-6.70*** (0.75)
Pucca Road					-3.79*** (0.75)	-1.50** (0.74)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	27022	25116	27022	27022	26970	25091
R^2	0.02	0.03	0.05	0.05	0.02	0.08
# Clusters	147	146	147	147	147	146

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A25: Dependent variable: RGGVY (= 100). The sample is limited to districts in the Western Region. Standard errors clustered by constituency.

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.14*** (0.03)	-0.13*** (0.03)	-0.10*** (0.03)	-0.17*** (0.03)	-0.13*** (0.03)	-0.13*** (0.03)
Distance (log)		1.15** (0.49)				0.77* (0.45)
Domestic Electricity (2001)			-0.22*** (0.02)			-0.19*** (0.02)
Population (log)				-11.55*** (1.31)		-10.05*** (1.23)
Pucca Road					-7.98*** (1.33)	-2.49** (1.07)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	15098	13930	15098	15098	15017	13868
R^2	0.00	0.00	0.06	0.06	0.01	0.11
# Clusters	77	77	77	77	77	77

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A26: Dependent variable: RGGVY (= 100). The sample is limited to districts in the Central Region. Standard errors clustered by constituency.

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.17*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.16*** (0.02)
Distance (log)		0.90*** (0.27)				0.73*** (0.27)
Domestic Electricity (2001)			-0.12*** (0.01)			-0.11*** (0.01)
Population (log)				-5.15*** (0.50)		-4.52*** (0.47)
Pucca Road					-5.03*** (0.67)	-2.32*** (0.59)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	49976	47511	49976	49976	49817	47422
R^2	0.01	0.01	0.02	0.02	0.01	0.04
# Clusters	160	160	160	160	160	160

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A27: Dependent variable: RGGVY (= 100). The sample is limited to districts in the Eastern Region. Standard errors clustered by constituency.

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.33*** (0.05)	-0.33*** (0.05)	-0.26*** (0.04)	-0.27*** (0.05)	-0.33*** (0.05)	-0.23*** (0.04)
Distance (log)		2.00* (1.14)				2.12* (1.14)
Domestic Electricity (2001)			-0.23*** (0.02)			-0.20*** (0.02)
Population (log)				-9.85*** (1.17)		-9.40*** (1.39)
Pucca Road					-8.85*** (2.01)	-3.66* (1.93)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	4461	4126	4461	4461	4392	4073
R^2	0.02	0.02	0.08	0.08	0.03	0.14
# Clusters	24	24	24	24	24	24

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A28: Dependent variable: RGGVY (= 100). The sample is limited to districts in the Bundelkhand Region (south). Standard errors clustered by constituency.

A9 Additional Results

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	0.16*	0.14	0.13	0.12	0.11	0.04
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)
Distance (log)		-3.80*				-3.26
		(2.20)				(2.19)
Domestic Electricity (2001)			0.31***			0.23***
			(0.04)			(0.03)
Population (log)				40.66***		35.26***
				(2.01)		(2.07)
Pucca Road					79.13***	62.78***
					(7.29)	(7.79)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	95963	90236	95963	95963	95791	90110
R^2	0.00	0.00	0.00	0.02	0.01	0.03
# Clusters	402	401	402	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A29: Dependent variable: average hours of power supply per day (rescaled to 0 – 2400 for readability). Standard errors clustered by constituency.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.19*** (0.02)	-0.18*** (0.02)	-0.17*** (0.02)	-0.18*** (0.02)	-0.18*** (0.02)	-0.16*** (0.02)
Wealth Index	-3.78*** (0.69)	-3.93*** (0.69)	-3.94*** (0.68)	-3.36*** (0.69)	-3.80*** (0.70)	-3.67*** (0.69)
Literacy Rate (%)	-0.45*** (0.05)	-0.45*** (0.05)	-0.43*** (0.05)	-0.50*** (0.05)	-0.45*** (0.05)	-0.48*** (0.05)
# Coop Commercial Banks	-12.87*** (1.41)	-12.54*** (1.45)	-12.94*** (1.39)	-5.41*** (1.21)	-12.20*** (1.37)	-5.79*** (1.25)
Irrigated Land (log)	-1.14*** (0.21)	-1.17*** (0.21)	-1.06*** (0.21)	-0.31 (0.22)	-1.08*** (0.21)	-0.36* (0.21)
Mean Light	-1.71*** (0.15)	-1.63*** (0.15)	-1.72*** (0.15)	-1.58*** (0.14)	-1.68*** (0.15)	-1.51*** (0.15)
Distance (log)		2.02*** (0.47)				2.16*** (0.44)
Domestic Electricity (2001)			-0.15*** (0.01)			-0.14*** (0.01)
Population (log)				-6.08*** (0.48)		-5.30*** (0.46)
Pucca Road					-4.70*** (0.88)	-2.19*** (0.83)
Constant	69.88*** (2.91)	64.87*** (3.17)	73.68*** (2.82)	111.15*** (4.21)	72.22*** (2.88)	104.98*** (4.46)
Observations	96557	90683	96557	96557	96196	90454
R ²	0.05	0.05	0.07	0.06	0.05	0.09
# Clusters	402	401	402	402	402	401

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.22*** (0.01)	-0.22*** (0.01)	-0.21*** (0.01)	-0.22*** (0.01)	-0.22*** (0.01)	-0.20*** (0.01)
Wealth Index	-1.85*** (0.24)	-1.86*** (0.24)	-1.80*** (0.23)	-1.61*** (0.23)	-1.87*** (0.23)	-1.59*** (0.22)
Literacy Rate (%)	-0.41*** (0.03)	-0.42*** (0.03)	-0.37*** (0.03)	-0.44*** (0.03)	-0.41*** (0.03)	-0.41*** (0.03)
# Coop Commercial Banks	-12.60*** (1.04)	-12.28*** (1.07)	-12.97*** (1.06)	-5.54*** (0.95)	-12.10*** (1.03)	-6.08*** (0.99)
Irrigated Land (log)	-1.17*** (0.11)	-1.18*** (0.12)	-1.04*** (0.11)	-0.24** (0.10)	-1.11*** (0.11)	-0.20** (0.10)
Mean Light	-0.98*** (0.10)	-0.92*** (0.10)	-0.94*** (0.09)	-0.89*** (0.10)	-0.98*** (0.09)	-0.81*** (0.10)
Distance (log)		0.86*** (0.20)				0.69*** (0.20)
Domestic Electricity (2001)			-0.14*** (0.01)			-0.13*** (0.01)
Population (log)				-6.47*** (0.39)		-5.81*** (0.38)
Pucca Road					-4.80*** (0.45)	-2.09*** (0.41)
Constant	66.54*** (1.73)	64.79*** (1.82)	68.28*** (1.66)	109.13*** (3.47)	69.42*** (1.79)	106.33*** (3.30)
Observations	96557	90683	96557	96557	96196	90454
R ²	0.03	0.03	0.05	0.05	0.03	0.07
# Clusters	402	401	402	402	402	401
Constituency FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A30: Dependent variable: RGGVY (if present, RGGVY= 100). The standard errors are clustered by constituency. Additional control variables (pre-RGGVY) for wealth and wealth-related confounders: literacy rate (%), number of cooperative commercial banks, irrigated land area (logarithmized), population (logarithmized), average decadal (1995-2004) nighttime luminosity in digital number on a 0-64 scale, with higher values indicating more light. All variables are from the 2001 Census of India, except night lights are from NOAA satellites.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.18*** (0.05)	-0.17*** (0.05)	-0.16*** (0.05)	-0.18*** (0.05)	-0.17*** (0.05)	-0.15*** (0.05)
Margin of Victory	-0.41 (0.38)	-0.41 (0.39)	-0.38 (0.37)	-0.46 (0.37)	-0.37 (0.37)	-0.42 (0.36)
Margin*Share SC	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Distance (log)		2.52*** (0.73)				2.53*** (0.70)
Domestic Electricity (2001)			-0.16*** (0.02)			-0.14*** (0.01)
Population (log)				-6.73*** (0.84)		-5.78*** (0.84)
Pucca Road					-6.78*** (1.59)	-3.00* (1.62)
Constant	36.31*** (3.66)	30.49*** (4.04)	40.99*** (3.80)	82.43*** (7.69)	40.45*** (3.50)	76.12*** (7.58)
Observations	25556	23877	25556	25556	25455	23829
R^2	0.01	0.01	0.03	0.03	0.01	0.06
# Clusters	98	98	98	98	98	98
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.20*** (0.03)	-0.20*** (0.03)	-0.19*** (0.03)	-0.20*** (0.03)	-0.19*** (0.03)	-0.19*** (0.03)
Margin*Share SC	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Distance (log)		1.28*** (0.44)				1.08** (0.42)
Domestic Electricity (2001)			-0.14*** (0.02)			-0.13*** (0.01)
Population (log)				-7.05*** (0.73)		-6.12*** (0.66)
Pucca Road					-6.35*** (0.89)	-3.17*** (0.77)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	25556	23877	25556	25556	25455	23829
R^2	0.01	0.01	0.03	0.04	0.01	0.06
# Clusters	98	98	98	98	98	98

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A31: Safe vs. marginal seats. Dependent variable: RGGVY (if present, RGGVY= 100). The standard errors are clustered by constituency. The sample is limited to cases in which a BSP member won.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.16*** (0.02)	-0.16*** (0.02)	-0.14*** (0.02)	-0.16*** (0.02)	-0.15*** (0.02)	-0.13*** (0.02)
Distance (log)		3.15*** (0.48)				3.26*** (0.46)
Domestic Electricity (2001)			-0.16*** (0.01)			-0.14*** (0.01)
Population (log)				-6.52*** (0.50)		-5.66*** (0.48)
Pucca Road					-6.48*** (1.00)	-3.61*** (0.96)
Constant	34.95*** (1.31)	27.38*** (1.58)	40.14*** (1.45)	79.87*** (3.95)	39.10*** (1.33)	73.07*** (4.09)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.03	0.03	0.01	0.06
# Clusters	402	401	402	402	402	401
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.21*** (0.01)	-0.21*** (0.01)	-0.19*** (0.01)	-0.20*** (0.01)	-0.21*** (0.01)	-0.19*** (0.01)
Distance (log)		1.34*** (0.22)				1.10*** (0.21)
Domestic Electricity (2001)			-0.15*** (0.01)			-0.13*** (0.01)
Population (log)				-6.64*** (0.40)		-5.94*** (0.38)
Pucca Road					-5.41*** (0.47)	-2.31*** (0.42)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.04	0.04	0.01	0.06
# Clusters	402	401	402	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A32: Dependent variable: RGGVY (if present, RGGVY= 100). We report the effect of scheduled castes (instead of the combined number of scheduled tribes and scheduled castes). The standard errors are clustered by constituency.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share ST (%)	-0.31*** (0.05)	-0.31*** (0.05)	-0.32*** (0.05)	-0.33*** (0.06)	-0.32*** (0.05)	-0.35*** (0.05)
Distance (log)		3.14*** (0.47)				3.26*** (0.45)
Domestic Electricity (2001)			-0.16*** (0.01)			-0.15*** (0.01)
Population (log)				-6.59*** (0.50)		-5.68*** (0.48)
Pucca Road					-6.88*** (1.00)	-3.92*** (0.97)
Constant	31.30*** (1.21)	23.88*** (1.46)	37.06*** (1.36)	76.86*** (3.80)	35.90*** (1.25)	70.62*** (3.96)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.00	0.01	0.03	0.03	0.01	0.06
# Clusters	402	401	402	402	402	401
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share ST (%)	-0.15** (0.07)	-0.14* (0.07)	-0.17** (0.07)	-0.15** (0.06)	-0.16** (0.07)	-0.17** (0.07)
Distance (log)		1.40*** (0.22)				1.15*** (0.21)
Domestic Electricity (2001)			-0.15*** (0.01)			-0.14*** (0.01)
Population (log)				-6.72*** (0.40)		-5.97*** (0.38)
Pucca Road					-5.76*** (0.48)	-2.58*** (0.42)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	96557	90683	96557	96557	96196	90454
R^2	0.00	0.00	0.03	0.03	0.00	0.05
# Clusters	402	401	402	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A33: Dependent variable: RGGVY (if present, RGGVY= 100). We report the effect of scheduled tribes (instead of the combined number of scheduled tribes and scheduled castes). The standard errors are clustered by constituency.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC in 2001 (%)	-0.18*** (0.02)	-0.17*** (0.02)	-0.16*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.15*** (0.02)
Distance (log)		3.15*** (0.47)				3.25*** (0.46)
Domestic Electricity (2001)			-0.16*** (0.01)			-0.14*** (0.01)
Population (log)				-6.55*** (0.50)		-5.69*** (0.49)
Pucca Road					-6.47*** (0.99)	-3.56*** (0.96)
Constant	35.40*** (1.33)	27.84*** (1.60)	40.59*** (1.47)	80.62*** (3.97)	39.56*** (1.36)	73.83*** (4.12)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.03	0.03	0.01	0.06
# Clusters	402	401	402	402	402	401
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC in 2001 (%)	-0.21*** (0.01)	-0.21*** (0.01)	-0.20*** (0.01)	-0.21*** (0.01)	-0.21*** (0.01)	-0.19*** (0.01)
Distance (log)		1.34*** (0.22)				1.10*** (0.21)
Domestic Electricity (2001)			-0.15*** (0.01)			-0.13*** (0.01)
Population (log)				-6.67*** (0.40)		-5.96*** (0.38)
Pucca Road					-5.44*** (0.47)	-2.32*** (0.42)
Constituency FE	✓	✓	✓	✓	✓	✓
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.04	0.04	0.01	0.06
# Clusters	402	401	402	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A34: Dependent variable: RGGVY (if present, RGGVY= 100). The data for the share of SC come from the 2001 Census instead of the 2011 one. The correlation between 2001 and 2011 share of SC is 0.92. The standard errors are clustered by constituency.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.30*** (0.06)	-0.30*** (0.06)	-0.24*** (0.06)	0.05 (0.06)	-0.26*** (0.06)	0.08 (0.06)
Share SC (square)	0.00** (0.00)	0.00*** (0.00)	0.00 (0.00)	-0.00*** (0.00)	0.00* (0.00)	-0.00*** (0.00)
Distance (log)		3.19*** (0.47)				3.20*** (0.45)
Domestic Electricity (2001)			-0.16*** (0.01)			-0.14*** (0.01)
Population (log)				-7.20*** (0.49)		-6.36*** (0.48)
Pucca Road					-6.33*** (0.98)	-3.61*** (0.96)
Constant	36.73*** (1.37)	29.12*** (1.74)	41.43*** (1.50)	82.65*** (3.93)	40.46*** (1.42)	76.11*** (4.06)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.03	0.03	0.01	0.06
# Clusters	402	401	402	402	402	401
Standard errors in parentheses						
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$						
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.46*** (0.03)	-0.46*** (0.03)	-0.42*** (0.03)	-0.13*** (0.02)	-0.44*** (0.03)	-0.12*** (0.02)
Share SC (square)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	-0.00*** (0.00)	0.00*** (0.00)	-0.00*** (0.00)
Distance (log)		1.36*** (0.22)				1.10*** (0.21)
Domestic Electricity (2001)			-0.14*** (0.01)			-0.13*** (0.01)
Population (log)				-6.87*** (0.40)		-6.15*** (0.39)
Pucca Road					-5.09*** (0.46)	-2.34*** (0.42)
Constant	38.98*** (0.43)	35.84*** (0.63)	43.44*** (0.53)	82.71*** (2.88)	42.11*** (0.58)	81.16*** (2.88)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.04	0.04	0.01	0.06
# Clusters	402	401	402	402	402	401
Constituency FE	✓	✓	✓	✓	✓	✓
Standard errors in parentheses						
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$						

Table A35: Quadratic effect of SC share. Dependent variable: RGGVY (if present, RGGVY= 100). The standard errors are clustered by constituency.

Pooled

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Distance (log)		0.15*** (0.02)				0.16*** (0.02)
Domestic Electricity (2001)			-0.01*** (0.00)			-0.01*** (0.00)
Population (log)				-0.30*** (0.02)		-0.26*** (0.02)
Pucca Road					-0.30*** (0.05)	-0.17*** (0.05)
Constant	-0.59*** (0.06)	-0.96*** (0.08)	-0.35*** (0.06)	1.43*** (0.18)	-0.40*** (0.06)	1.12*** (0.19)
Observations	96557	90683	96557	96557	96196	90454
# Clusters	402	401	402	402	402	401

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A36: Logit specification. Dependent variable: RGGVY (if present, RGGVY= 1). Note: fixed effect versions are computationally too intensive, given the large number of parameters. The standard errors are clustered by constituency.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC [0,1]	-0.28 (0.21)	-0.26 (0.20)	-0.28 (0.21)	-0.30 (0.21)	-0.33 (0.21)	-0.31 (0.20)
Distance (log)		-0.53*** (0.06)				-0.55*** (0.06)
Domestic Electricity (2001)			0.00 (0.00)			-0.00 (0.00)
Population (log)				0.30*** (0.05)		0.26*** (0.04)
Pucca Road					0.51*** (0.14)	0.41*** (0.13)
Constant	2.58*** (0.14)	3.83*** (0.25)	2.57*** (0.14)	0.52 (0.33)	2.26*** (0.16)	1.80*** (0.40)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.00	0.02	0.00	0.01	0.00	0.04
# Clusters	402	401	402	402	402	401
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$						
Constituency fixed effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC [0,1]	0.02 (0.12)	-0.02 (0.13)	0.01 (0.13)	0.01 (0.12)	0.01 (0.13)	-0.03 (0.13)
Distance (log)		-0.44*** (0.05)				-0.43*** (0.05)
Domestic Electricity (2001)			0.00*** (0.00)			0.00** (0.00)
Population (log)				0.08*** (0.02)		0.08*** (0.02)
Pucca Road					-0.01 (0.04)	-0.03 (0.04)
Constant	2.51*** (0.03)	3.54*** (0.11)	2.48*** (0.03)	1.94*** (0.11)	2.52*** (0.04)	2.98*** (0.14)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.00	0.03	0.00	0.00	0.00	0.03
# Clusters	402	401	402	402	402	401
Constituency FE	✓	✓	✓	✓	✓	✓
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$						

Table A37: Effect of SC share on night-time lighting. Dependent variable: average night-time light. Note: the share of SC is rescaled to the [0, 1] interval to make point estimates more readable. The standard errors are clustered by constituency.

Pooled					
	(1)	(2)	(3)	(4)	(5)
Share SC (%)	0.11*** (0.02)	0.10*** (0.02)	0.10*** (0.02)	0.10*** (0.02)	0.09*** (0.02)
Distance (log)		2.46*** (0.50)			2.29*** (0.47)
Domestic Electricity (2001)			0.03*** (0.01)		0.01 (0.01)
Population (log)				9.72*** (0.48)	9.60*** (0.50)
Constant	63.78*** (1.76)	57.30*** (2.51)	62.86*** (1.79)	-3.22 (4.37)	-8.59* (4.88)
Observations	96196	90454	96196	96196	90454
R^2	0.00	0.01	0.00	0.05	0.05
# Clusters	402	401	402	402	401
Standard errors in parentheses					
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$					
Constituency fixed effects					
	(1)	(2)	(3)	(4)	(5)
Share SC (%)	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.05*** (0.01)
Distance (log)		0.46** (0.23)			0.62*** (0.22)
Domestic Electricity (2001)			0.03*** (0.00)		0.01*** (0.00)
Population (log)				7.59*** (0.25)	7.48*** (0.25)
Constant	64.77*** (0.23)	63.09*** (0.58)	63.92*** (0.27)	12.49*** (1.74)	10.96*** (1.89)
Observations	96196	90454	96196	96196	90454
R^2	0.00	0.00	0.00	0.04	0.04
# Clusters	402	401	402	402	401
Constituency FE	✓	✓	✓	✓	✓
Standard errors in parentheses					
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$					

Table A38: Dependent variable: pucca road (if present, pucca= 100). The standard errors are clustered by constituency.

Pooled

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.18*** (0.04)	-0.17*** (0.04)	-0.16*** (0.04)	-0.17*** (0.04)	-0.17*** (0.04)	-0.15*** (0.04)
Distance (log)		3.15*** (0.82)				3.26*** (0.77)
Domestic Electricity (2001)			-0.16*** (0.02)			-0.14*** (0.02)
Population (log)				-6.53*** (0.93)		-5.67*** (0.92)
Pucca Road					-6.48*** (2.00)	-3.59* (1.92)
Constant	35.43*** (2.70)	27.86*** (2.72)	40.64*** (2.95)	80.42*** (7.36)	39.60*** (2.54)	73.64*** (7.91)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.01	0.03	0.03	0.01	0.06
# Clusters	70	70	70	70	70	70

Standard errors in parentheses

 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Constituency fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.21*** (0.02)	-0.21*** (0.02)	-0.20*** (0.02)	-0.20*** (0.02)	-0.21*** (0.02)	-0.19*** (0.02)
Distance (log)		1.35*** (0.26)				1.10*** (0.24)
Domestic Electricity (2001)			-0.15*** (0.02)			-0.13*** (0.01)
Population (log)				-6.64*** (0.78)		-5.93*** (0.73)
Pucca Road					-5.44*** (0.72)	-2.34*** (0.55)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.21	0.21	0.23	0.23	0.21	0.25
# Clusters	70	70	70	70	70	70
Constituency FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A39: Dependent variable: RGGVY (if present, RGGVY= 100). The standard errors are clustered by district.

	Unelectrified in 2001					Electrified in 2001				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share SC (%)	-0.20*** (0.02)	-0.20*** (0.02)	-0.19*** (0.02)	-0.20*** (0.02)	-0.19*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)	-0.17*** (0.02)
Distance (log)		1.49*** (0.31)			1.34*** (0.30)		0.54*** (0.19)			0.52*** (0.18)
Population (log)			-6.08*** (0.76)		-5.86*** (0.78)			-4.73*** (0.69)		-4.65*** (0.68)
Pucca Road				-6.11*** (0.73)	-3.18*** (0.61)				-1.67*** (0.69)	-0.13 (0.62)
Observations	61950	58245	61950	61724	58104	34605	32435	34605	34471	32348
R ²	0.23	0.23	0.25	0.23	0.25	0.23	0.23	0.24	0.23	0.25
# Clusters	70	70	70	70	70	70	70	70	70	70
Constituency FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A40: Dependent variable: RGGVY (if present, RGGVY= 100). All models estimated with constituency fixed effects. The standard errors are clustered by district.

Pooled						
	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)
Distance (log)		-2.13*** (0.34)				-2.15*** (0.33)
Domestic Electricity (2001)			0.00 (0.01)			0.00 (0.01)
Population (log)				-0.73 (0.47)		-0.96* (0.49)
Pucca Road					0.86 (1.42)	1.44 (1.51)
Constant	25.57*** (1.46)	30.66*** (1.73)	25.53*** (1.53)	30.59*** (2.83)	25.05*** (1.66)	36.30*** (3.13)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.01	0.02	0.01	0.01	0.01	0.02
# Clusters	70	70	70	70	70	70

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Constituency fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Share SC (%)	-0.08*** (0.01)	-0.09*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.09*** (0.01)
Distance (log)		-1.52*** (0.14)				-1.54*** (0.14)
Domestic Electricity (2001)			0.01** (0.00)			0.01** (0.00)
Population (log)				-0.77*** (0.24)		-0.97*** (0.25)
Pucca Road					0.74*** (0.22)	1.16*** (0.22)
Observations	96557	90683	96557	96557	96196	90454
R^2	0.30	0.29	0.30	0.30	0.30	0.30
# Clusters	70	70	70	70	70	70
Constituency FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A41: Dependent variable: household electrification in 2011 (0-100 percent). The standard errors are clustered by district.

Spatial Autoregressive Models (Part I)

District	Point estimate (Share SC)	Standard error	t-value
Agra	-0.37	0.06	-6.44
Aligarh	-0.41	0.06	-6.29
Allahabad	-0.27	0.05	-5.69
Ambedkar Nagar	-0.07	0.03	-2.21
Auraiya	-0.32	0.08	-4.05
Azamgarh	-0.24	0.03	-7.32
Baghpat	-	-	-
Bahraich	-0.15	0.10	-1.50
Ballia	-0.22	0.05	-4.23
Balrampur	-0.23	0.08	-3.00
Banda	-0.50	0.12	-4.31
Barabanki	-0.17	0.06	-2.83
Bareilly	-0.37	0.05	-7.50
Basti	-0.16	0.05	-3.38
Bijnor	-0.21	0.03	-7.63
Budaun	-0.47	0.04	-10.87
Bulandshahar	-0.25	0.06	-4.32
Chandauli	-0.01	0.05	-0.12
Chitrakoot	-0.36	0.09	-3.97
Deoria	-0.15	0.04	-3.56
Etah	-0.81	0.06	-13.75
Etawah	-0.42	0.08	-4.93
Faizabad	-0.33	0.08	-4.15
Farrukhabad	-0.42	0.09	-4.82
Fatehpur	-0.18	0.08	-2.15
Firozabad	-0.63	0.07	-8.73
Gautam Buddha Nagar	-0.28	0.12	-2.29
Ghaziabad	0.07	0.05	1.45
Ghazipur	-0.08	0.02	-3.92
Gonda	-0.55	0.08	-6.49
Gorakhpur	-0.17	0.03	-5.45
Hamirpur	-0.61	0.16	-3.69
Hardoi	-0.23	0.05	-4.43
Hathras	-0.29	0.07	-4.44

Table A42: Estimates from a spatial autoregressive model (part I). Estimates computed state-by-state due to the size of the spatial correlation matrix. Models could not converge in a few cases.

Spatial Autoregressive Models (Part II)

District	Point estimate (Share SC)	Standard error	t-value
Jalaun	-0.21	0.06	-3.39
Jaunpur	-0.12	0.03	-3.93
Jhansi	-0.33	0.11	-2.95
Jyotiba Phule Nagar	-0.29	0.08	-3.75
Kannauj	-0.41	0.10	-4.08
Kanpur Dehat	-0.35	0.09	-4.12
Kanpur Nagar	-0.18	0.07	-2.71
Kaushambi	-0.37	0.09	-3.97
Kheri	-0.03	0.05	-0.71
Kushinagar	-0.23	0.08	-2.95
Lalitpur	-0.23	0.12	-1.87
Lucknow	0.05	0.04	1.12
Mahoba	-0.21	0.15	-1.38
Mahrajganj	-0.23	0.10	-2.38
Mainpuri	-0.42	0.09	-4.49
Mathura	-0.04	0.05	-0.82
Mau	-0.11	0.05	-2.29
Meerut	-	-	-
Mirzapur	0.00	0.05	0.02
Moradabad	-0.26	0.04	-6.35
Muzaffarnagar	-	-	-
Pilibhit	-0.24	0.07	-3.56
Pratapgarh	-0.17	0.06	-2.92
Rae Bareli	-0.06	0.04	-1.63
Rampur	-0.23	0.07	-3.51
Saharanpur	-	-	-
Sant Kabir Nagar	-0.16	0.06	-2.72
Sant Ravidas Nagar	-0.03	0.05	-0.74
Shahjahanpur	-0.34	0.04	-8.73
Shrawasti	-0.51	0.13	-4.03
Siddharthnagar	-0.34	0.06	-5.50
Sitapur	-0.21	0.05	-4.12
Sonbhadra	-0.31	0.05	-6.89
Sultanpur	-0.09	0.05	-1.65
Unnao	-0.18	0.06	-3.02
Varanasi	-	-	-

Table A43: Estimates from a spatial autoregressive model (part II). Estimates computed state-by-state due to the size of the spatial correlation matrix. Models could not converge in a few cases.

A10 ACCESS Survey

A10.1 Summary Statistics

- Table A44 provides the summary statistics for the ACCESS data used in the analysis.
- Table A45 reports the estimates of SC status on knowledge about RGGVY and household electrification.

	Mean	S.D.	Min.	Max.	Obs.
Heard of RGGVY	0.24	0.43	0	1	3023
Electrified (Grid)	0.57	0.49	0	1	3023
SC/ST	0.22	0.41	0	1	3023

Table A44: Summary statistics for ACCESS data used in the analysis.

A10.2 Evidence from Household Surveys

This section looks below the village level at the experiences of Dalit and non-Dalit households in Uttar Pradesh. We examine whether our community-level findings hold when we focus on individual households.

Collected between November 2014 and May 2015, the ACCESS survey data includes information from a representative sample of 252 villages from 21 districts (Aklin et al., 2016). The survey is useful because it contains questions about grid electrification status, awareness about RGGVY (i.e., whether the household head has heard of the scheme), and whether the household is Dalit or non-Dalit.

Table A45 uses the ACCESS survey to examine grid electricity connections, RGGVY awareness, and SC status. Models 1 and 4 are linear; models 2 and 4 are logistic regressions; models 3 and 6 are logistic regressions with conditional fixed effects. Standard errors are adjusted for sampling by village. As the table shows, SC households perform systematically worse than non-SC households. In model 1, we see that Dalit households are 4 percentage points less likely to have heard from the RGGVY, suggesting that RGGVY implementation is concentrated outside villages and habitations populated by Dalits. In model 4, we see that Dalit households are 15 percentage points less likely

	Heard of RGGVY			Electrified (Grid)		
	OLS	Logit	FE Logit	OLS	Logit	FE Logit
SC	-0.04** (0.02)	-0.25** (0.12)	-0.29** (0.14)	-0.15*** (0.02)	-0.60*** (0.09)	-0.76*** (0.11)
<i>N</i>	3023	3023	2255	3023	3023	2711
Villages	252	252	188	252	252	226

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A45: SC households, awareness of RGGVY (models 1-2), and household grid electricity. Models 2 and 4 are logistic regressions with sampling weights; models 3 and 6 are logistic regressions with conditional fixed effects at the village level. Standard errors are adjusted for sampling by village.

to have grid electricity connections, again consistent with the notion that the lack of RGGVY implementation is hurting Dalit households. Indeed, because this pattern is robust at the household level, the unequal pattern cannot be attributed to ecological inference problems.

Supplementary Appendix: References

- Aklin, Michaël, Chao-yo Cheng, Johannes Urpelainen, Karthik Ganesan, and Abhishek Jain. 2016. “Factors Affecting Household Satisfaction with Electricity Supply in Rural India.” *Nature Energy* 1 (16170).
- Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist’s Companion*. Princeton: Princeton University Press.
- Imbens, Guido W., and Thomas Lemieux. 2008. “Regression Discontinuity Designs: A Guide to Practice.” *Journal of Econometrics* 142 (2): 615-635.
- McCrary, Justin. 2008. “Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test.” *Journal of Econometrics* 142 (2): 698-714.