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# Geographic and socio-economic barriers to rural electrification: New evidence from Indian villages[☆]

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ABSTRACT

The International Energy Agency estimates that more than a billion people remain without household electricity access. However, countries such as India have recently made major progress in rural electrification. Who has benefited from these achievements? We focus on 714 villages in six energy-poor states of northern and eastern India to investigate trends in electricity access. We use data both from the 2011 Census of India and an original energy access survey conducted in 2014 and 2015. During the three years that separated the surveys, distance to the nearest town and land area lose their power as predictors of the percentage of households in the village that has access to electricity. In this regard, the Indian government's flagship rural electrification program seems to have managed to overcome a major obstacle to grid extension. On the other hand, socio-economic inequalities between villages related to caste status and household expenditure remain strong predictors. These findings highlight the importance of socio-economic barriers to rural electricity access and alleviate concerns about remoteness and population density as obstacles to grid extension.

## 1. Introduction

The lack of electricity access is a major obstacle to socio-economic development (Cabraal et al., 2005; Cook et al., 2005; Bernard, 2010; Dinkelman, 2011) and to this date, more than a billion people in developing countries remain without household electricity access (International Energy Agency, 2014). There are signs of progress, however. Between 2002 and 2012, the percentage of households with electricity access increased from 64% to 76% worldwide (International Energy Agency, 2014). In India, census data show that the percentage of households with electricity access increased from 56% to 67%; even in rural areas, where electricity access is a more severe problem, electricity access increased from 43.5% to 55.3% (Government of India, 2011). However, these encouraging patterns hide considerable variation across villages. Who has benefited from India's rural electrification drive? Who remains without power? How have these improvements been achieved?

The goal of this article is to investigate patterns of rural electrification in India. By conducting the analysis, we provide new insights into why and how certain rural communities but not others have come to enjoy improved rates of electricity access. Using data from the 2011 Census of India and an original survey with 8568 respondents conducted in 714 villages in 2014 and 2015, we examine the role of geographic and socio-economic factors in rural electrification.[1] Our primary outcome variable is the percentage of households electrified within each village. The analysis focuses on six states (Bihar, Jharkhand, Madhya Pradesh, Odisha, Uttar Pradesh, and West Bengal) in northern and eastern India. As these six contiguous states have high levels of energy poverty relative to other states and are inhabited by a population of almost 500 million people, understanding the progress of rural electrification within them is central to understanding India's overall progress toward universal electricity access and service. While other states also face the challenge of rural electrification, these six states contained the largest numbers of non-electrified households at the time of the survey. We also exploit data on the implementation of India's flagship rural electrification program, the Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY), to evaluate the role of public policy in improvements in electricity access. By explicitly linking improved electricity access and national policy, we can see to what extent government policy has contributed to enhanced rural electrification.

The results of the statistical analysis show that geographic inequal-

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[1] From the census we use only observations corresponding to the villages present in the original survey, that is 714 villages.

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ities of electricity access have significantly decreased since the 2011 census. In the three years before the original survey, distance to the nearest city and the surface area of the village have lost almost all of their predictive power for the percentage of household electricity access. When we use the 2011 census data, these variables are strong predictors of the percentage of electrified households; when we use the more recent data, they no longer predict rates of electricity access. The distribution of electricity access has become more even across the territory as many more remote rural communities now enjoy improved rates of access. This trend can probably be jointly explained by India's rural electrification policy and continued economic growth in rural areas.

On the other hand, inequalities between villages remain stark with respect to wealth and caste composition. Both in the 2011 census data and in the 2014–2015 survey, there is a large difference in electricity access between villages populated by upper and lower caste households. In both samples, the number of upper caste households is a strong predictor of electricity access, whereas the number of lower caste households is either not correlated with electricity access in the village (in the 2015 survey) or its coefficient is about half the size the one for upper caste (in the census data). Similarly, access to electricity across villages continues to be highly dependent on average expenditure within villages, despite the RGGVY's emphasis on providing free connections to households below the poverty line. It is possible that RGGVY prioritized households below the poverty line within villages that are not the poorest. In any case, the provision of free connections appears not to have changed a reality in which the wealthier villages enjoy much better access than their poorer counterparts. Analysis of household data within villages also shows that even controlling for household wealth, lower caste households are about 15% points less likely to have an electric connection than upper caste households living in the same village. Finally, we find evidence for a strong relationship between the quality of electricity service, measured as hours of electricity available on a daily basis, and wealth at the village level.

These results support the idea that India's recent rural electrification drive has been successful in bringing electricity to remote and small rural communities. Rates of electricity access have increased significantly and, after more than half a century of independence, universal electrification is in sight. Neither distance to the closest town nor the geographic area of a village predicts electrification rates today. At the same time, there remains a gap between upper and lower castes, as well as wealthy and poor areas. In this regard, the next frontier for India's electrification effort should be to reduce inequalities of electricity access with respect to social and economic characteristics. The literature on rural electrification has consistently emphasized that small and remote communities face difficulty in gaining access to the national electric grid (Sinha et al., 1991; Mahapatra and Dasappa, 2012; Urpelainen, 2014; Slough et al., 2015), and many scholars have called for increased attention to off-grid alternatives to grid extension (Kaundinya et al., 2009; Kumar et al., 2009; Alstone et al., 2015). Our findings on recent progress in grid extension suggest that in the Indian context, the government has managed to overcome the limitations of grid extension. Instead, the primary challenges appear to be in overcoming limitations related to socio-economic inequity and rural poverty.

The primary contributions of our study are twofold. First, we reach beyond income as a factor explaining variation in rural electrification and consider geographic and social factors. Studies such as Khandker et al. (2012) show a strong relationship between income and energy poverty in India, as the poorest households can only afford a minimal level of energy access, while (Alkon et al., 2016) find evidence of a high willingness to pay for modern energy in rural India, provided modern fuels are available. Golumbeanu and Barnes (2013), in turn, find that high household connection charges are a key obstacle to improved electricity access in Sub-Saharan Africa. At the macro level, Onyeji et al. (2012) consider the role of geography – in particular, population density – in explaining electricity access in Sub-Saharan Africa. While some studies (Oda and Tsujita, 2011) have considered social factors, such as the religious composition of villages in Bihar, as possible explanations for variation in rural electrification, ours is the first one to systematically examine the role of geography and society in rural electrification in a large, energy-poor area of India.

Second, we offer a dynamic picture of the role of these factors in rural electrification. Most studies explaining rural electrification and energy acccess (e.g., Oda and Tsujita (2011); Khandker et al. (2012); Onyeji et al. (2012)) are cross-sectional in nature. While they provide a snap shot of the extent and determinants of rural electrification at a given time, they do not show how the covariates of rural electrification have changed over time. Our findings show that although India's recent rural electrification drive has rapidly reduced geographic disparities in rural electrification, it has done much less to reduce disparities related to income or social status. This dynamic focus is particularly useful for informing policy implementation, as it allows us to describe and explain variegated progress in rural electrification.

## 2. Rural electrification in India

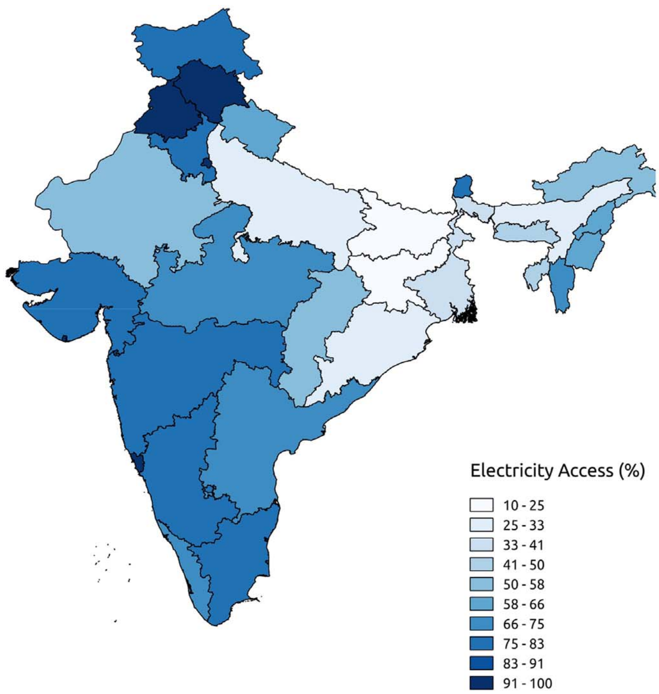
India's rural electrification situation has improved over time, but large numbers of rural households remain without a connection. The distribution of electricity access across Indian states in 2001 and 2011 is illustrated in Fig. 1. According to the Census of India, between 2001 and 2011, the percentage of households using grid electricity as their primary source of lighting increased from 55.8% to 67.2% (Government of India, 2011). However, the situation is significantly worse in rural areas where, in 2011, only 55.3% of households used grid electricity as their primary source of lighting; at the same time, 92.7% of urban households did so.

In the past decade, RGGVY has been the government's flagship rural electrification program.[2] Since April 2005, the government's goal has been to electrify all unelectrified villages in India, with the exception of a very small number of the most remote villages covered under a separate village electrification program. Besides unelectrified villages, RGGVY also operates in villages with poor electric infrastructure under a modality called "intensive electrification." Under the scheme, the central government covers 90% of the capital cost, while states are expected to contribute 10%. States must submit an application to the central government for RGGVY funds, commit to implementation, and propose a plan for doing so. State electric utilities then prepare plans for electrifying villages according to RGGVY guidelines, and quality of implementation is monitored both by the Ministry of Power and independent auditors. Any village with a population of 100 or more people is eligible for electrification. Furthermore, the RGGVY offers free household connections to households below the poverty line and considers 6 h per day a minimum requirement of supply. According to official government sources, by August 2015, RGGVY had reached 111,000 previously unelectrified villages and provided connections to 22,300,000 households below the poverty line.[3] This is a large number relative to the total number of villages in the 2011 census (640,000 in total; 600,000 inhabited), especially given that many of these villages in the wealthier parts of India were already fully electrified before the RGGVY began.

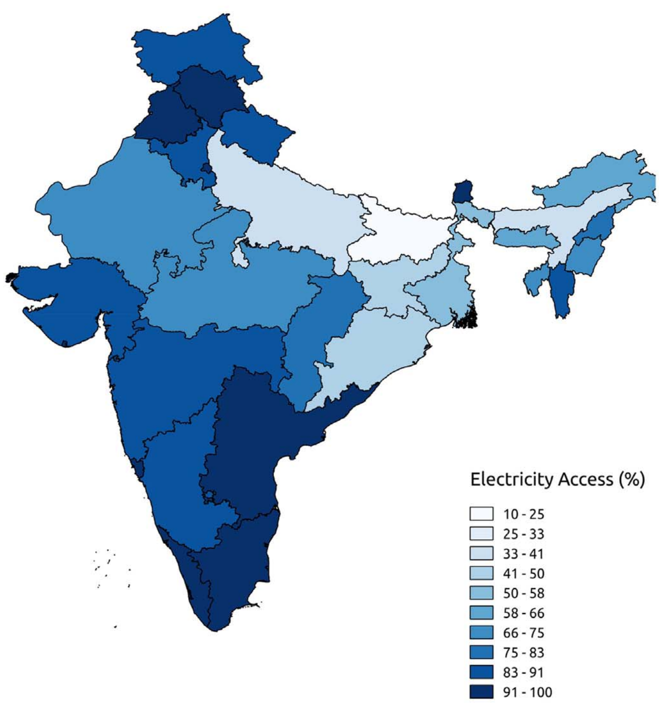
We examine the status and trends of rural electrification in six energy-poor areas of north India, with a particular emphasis on spatial and socio-economic determinants of rural electricity access. As for spatial factors, we consider both the distance between the village and the nearest city (logarithmized, kilometers) and the surface area of the village (logarithmized, hectares). These variables form the baseline for

[2] See summary at http://rggvy.gov.in/rggvy/rggvyportal/rggvy_glance.html (accessed October 25, 2015).

[3] See http://rggvy.gov.in/rggvy/rggvyportal/statewisesummary.jsp for progress reports for India and each individual state (accessed October 25, 2015).




(a) Census of 2001.




(b) Census of 2011.

**Fig. 1.** Electricity access (%) in Indian states, 2001 and 2011.

evaluating progress of rural electrification. The cost of grid extension increases rapidly as the distance between the community and the transmission network grows (Sinha et al., 1991; Oparaku, 2003; Mahapatra and Dasappa, 2012). Similarly, within a village, the challenge of last-mile electrification depends on how sparsely houses are spread. We obtain information for each village about the distance to the nearest city and total surface area of the village from the 2011 census and our sample shows significant variation in both variables. The average village is located about 14 km away from the nearest town and the maximum distance we found is 92 km. Similarly, the average village has a surface area of about 521 ha, with a maximum of 5419 ha.

No analysis of India's socio-economic development is complete without a consideration of the caste structure. Historically, the Indian society has been divided into a complex structure of hierarchically ranked, endogamous castes (Omvedt, 2006). Although the role of castes has not been analyzed in the context of rural electrification, there is a body of literature on the persistent gap in access to public goods and services between upper and lower castes (Betancourt and Gleason, 2000; Drèze and Amartya, 2002; Kijima, 2006; Kumar, 2013). Some recent studies also find that measures to bridge the gap, such as political reservations for former untouchables and tribal peoples (scheduled castes and scheduled tribes, respectively) have failed (Jensenius, 2015). At the same time, the past two decades have seen an outburst of lower-caste mobilization (Duncan, 1999; Jaffrelot, 2003; Kale and Mazaheri, 2014), often inspired by Dr. B.R. Ambedkar, the architect of India's constitution and the lower-caste leader of the Congress movement during India's independent struggle (Jaoul, 2006).

We obtain information about the caste structure of each village from the 2011 census and the 2014 survey. The 2011 census provides information about the number of people in the village that belongs to certain caste groups, while the 2014 survey provides information about the number of *households* in each village that belongs to certain caste groups. In our sample, the average village contains about 670 people from a scheduled caste, 180 from a scheduled tribe, and 2850 from other types. In the 2014 survey, the average village contains 94 households from a scheduled caste, 32 from a scheduled tribe, 281 from other backward castes, and 135 from general castes.

We also consider wealth levels within villages. An obvious obstacle to rural electrification is the inability of households to pay for the connection and the monthly fees of electricity use (Winkler et al., 2011; Lee et al., 2014; Alkon et al., 2016). Therefore, it is important to account for economic development in a village. This variable is not available in the 2011 census, but our original survey contains data on household monthly expenditure, which we aggregate at the village level. To ensure a normal distribution, we measure wealth as the logarithmized average monthly expenditure. In the average village, the average household spends about 5300 rupees (84 dollars) per month.[4] This village-level spending level ranges from 2125 to 11,333 across villages.

In assessing rural electrification in India, we also consider the quality of electricity service. Recent studies of energy access show that the quality of electricity service is important for understanding the benefits of electrification for rural income generation. If electricity access is limited to a few hours per day or unreliable, grid connectivity increases household incomes less than when the quality of electricity service is high (Chakravorty et al., 2014). Similarly, the hours of electricity available to households are strongly associated with people's subjective satisfaction with their electricity service (Aklin et al., 2016). Finally, the absence of electricity supply at peak demand – typically at night when rural households need lighting for cooking, dinner, and social activities – results in a major loss of welfare (Harish and Tongia, 2014).

Given the importance of the quality of electricity supply for rural life and livelihoods, we separately examine how it is related to geographic factors, social status, and wealth or income. By examining the extent to which the quality of electricity supply is associated with these factors, we can understand both the potential and limitations of rural electrification – grid extension – for poverty alleviation and social empowerment in rural India. If we find that rural electrification provides poor and socially marginalized communities with a low-quality electricity service, then grid extension itself may contribute

[4] On December 31, 2014, the exchange rate for Indian rupees to dollars was 63.2 to 1. See https://goo.gl/9Nix2f (accessed November 8, 2015).

less to socio-economic development than under conditions of better service.

## 3. Explaining village electrification rates

We analyze the determinants of electrification with respect to spatial and socio-economic factors using data from the 2011 census and from an original survey completed in 2014.[5] In the survey, 8568 households were interviewed in 714 villages, 51 districts and six states. Fig. 2 shows the geographic distribution of the study states and districts in India. More details on the sampling method, data collection, measurement, and statistical methods is available in Appendix A. For full summary statistics, see Supporting Information.

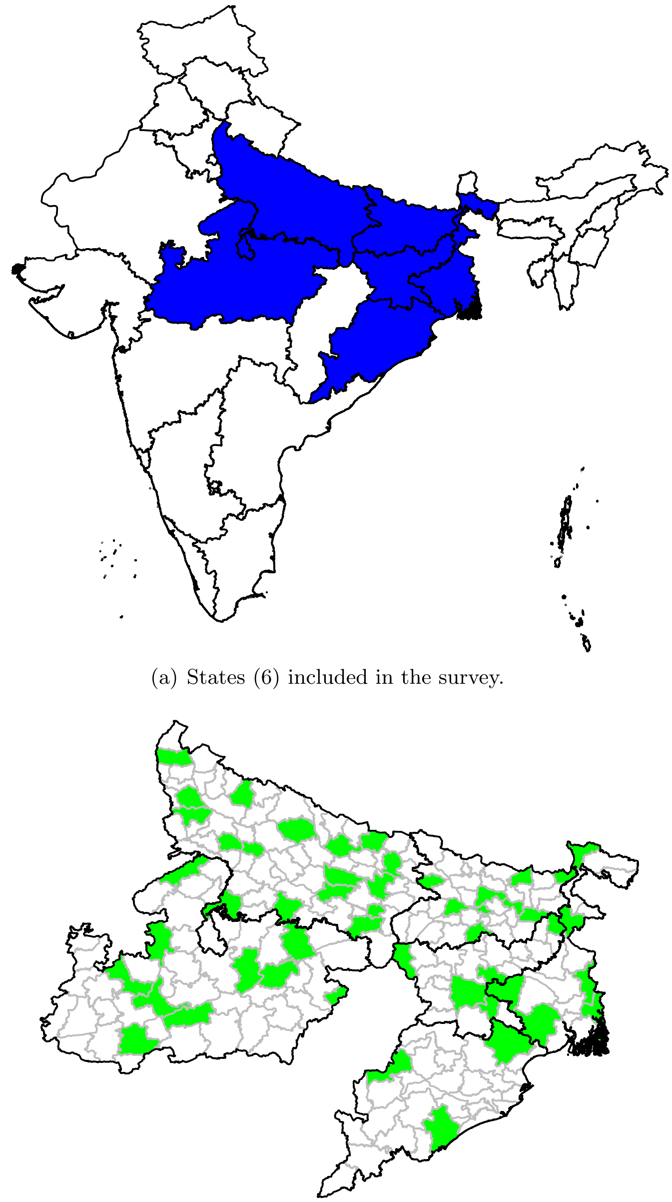
Our outcome variable of interest is electricity access, measured as the percentage (0–100) of households in a village that has access to electricity. When data from the 2011 census is used, the variable value is measured for the year 2011; when the original survey data are used, the variable value is measured for the year 2014 (see Data and methods for details of measurement). Because the 2014 survey included a village and a household survey, we are able to reconstruct two different electricity access variables, one based on the household survey and the other based on the village survey. Fig. 3 illustrates the distribution of village electrification in 2011 (census) and in 2014 (village questionnaire). Notably, electrification rates seem to have increased sharply, with a particularly large drop in the number of completely unelectrified villages. Histogram for the electricity access variable from the household questionnaire is available in the Supporting Information (Fig. S1).

Another variable of interest relates to the supply of electricity. From the 2014 household survey, for each village, we construct the average number of hours of electricity available per day, only including households with domestic electricity connections. Fig. 4 illustrates the distribution of this variable. We note that only a few villages have continuous electricity supply around the clock, while most villages get between 7 and 12 h of electricity a day. In the average village, households receive 11.4 h of electricity.

Table 1 displays the main regression results. The dependent variable is always electricity access (0–100) at the village level. To account for the sampling structure, we cluster standard errors at the district level. All models include the logarithmized population count of scheduled castes, scheduled tribes, and people belonging to other government castes. All models also include variables for monthly household expenditure, distance, surface area, and district fixed effects. In each regression, we make sure that the dependent variable and the independent variables for castes come from the same source of data: when the dependent variable is constructed using data from the 2011 census (respectively, 2014 survey), the castes variables used were also constructed using the 2011 census (respectively, 2014 survey). This is important because many changes in the caste structure of the village may have occurred between the census in 2011 and the survey in 2014.

Across all specifications, regardless of whether data from the 2011 census or the 2014 original survey were used, the level of expenditure is a strong and robust predictor of electricity access. Depending on the specification, increasing household expenditure by one logarithmized unit is associated with a 11–20% point increase in household electricity access rate. Another robust predictor of electricity access is the number of other types of population (neither scheduled caste nor scheduled tribe). While the coefficient varies across specifications, it is always significant and larger than that for scheduled caste or tribe. It seems that villages with upper caste households enjoy better rates of electricity access both in 2011 and in 2014.

On the other hand, the predictive powers of distance from town and land area decrease between 2011 and 2014. Both distance and area



(a) States (6) included in the survey.

(b) Districts (51) included in the survey.

**Fig. 2.** Geographic coverage of survey.

have large, statistically significant negative coefficients in the 2011 regressions (1–2), but the coefficients lose their statistical significance and become much smaller in the 2014 regressions (3–6). This evidence suggests that the roles of distance and population density in predicting household electricity access have decreased during the intervening three years. This potentially implies that the recent government programs for rural electrification have been successful at targeting remote areas (Bhattacharyya and Srivastava, 2009). Table S20 in the Supporting Information shows that results are fully robust with a fractional logit regression model.[6]

In every other model, we include a Herfindahl index of the fragmentation of households across habitations, expecting that access to electricity might be difficult to expand in villages with households distributed over many habitations. The variable ranges from 0 to 1, with higher values indicating less fragmentation. We find that the

[5] See Jain et al. (2015) and Aklin et al. (2016) for details of original survey. The data are freely available to anyone from Aklin et al. (2016b).

[6] A fractional logistic regression accounts for the boundaries of a percentage variable, allowing us to verify that the results from the linear estimation are not biased by completely non-electrified or fully electrified villages.

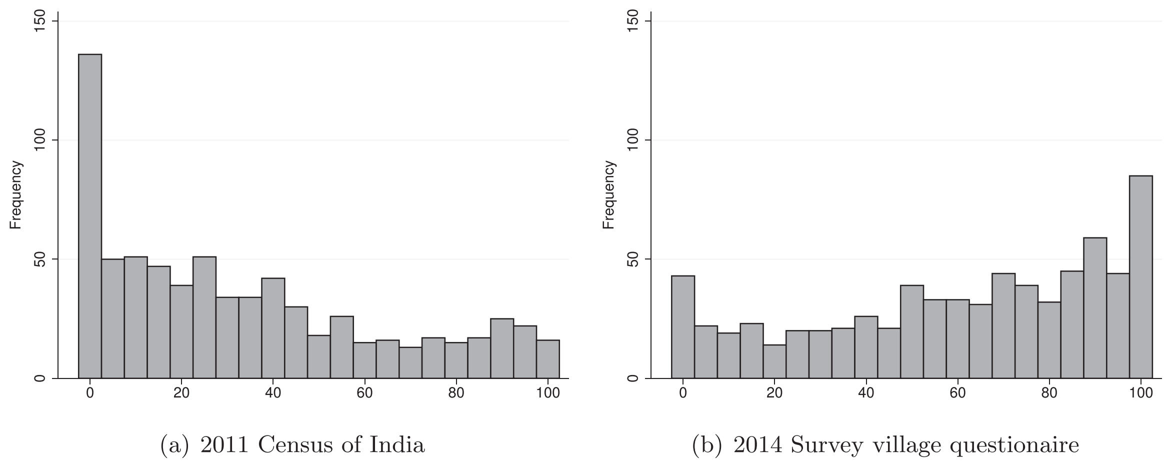



**Fig. 3.** Histogram of village electrification rate (%) in sample villages according to different data sources.

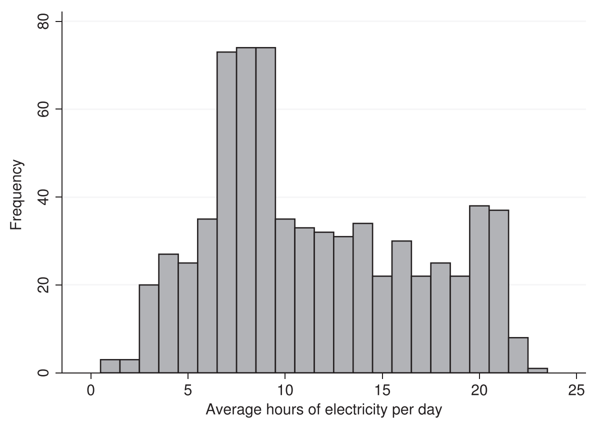



**Fig. 4.** Histogram of the average number of hours of electricity per day in sample villages.

coefficient is neither statistically significant nor particularly large, suggesting that fragmentation may not be a major obstacle to expanding electricity access. It is also possible that the surface area variable, which we also include, is a better proxy for dispersion than the Herfindahl index.

We also include in some models a gini coefficient for the distribution of household expenditure, as economic inequality may mean that poor households cannot afford to pay for electricity, even holding mean household expenditure in the village constant. The variable ranges from 0 to 1, with higher values indicating more within-village economic inequality. Again, though, the coefficient is not statistically significant or very large. We interpret this finding as suggesting that economic inequality may not be a major barrier to household electrification, especially as the coefficient on household expenditure itself is large and statistically significant, highlighting the importance of wealth itself.

In Table 2, we estimate the same models but use the number of hours of electricity available per day (0–24) among electrified households as the outcome variable. If anything, villages with many scheduled caste and tribe households tend to benefit from better electricity supply. As long as a village is electrified, lower-caste households do not seem to be disadvantaged. This result is not surprising, as the hours of electricity available depend largely on the supply of power to the rural feeder connected to the village, so that caste discrimination at the village level would be very difficult in practice. Fig. S2 of the Supporting Information confirms, in turn, that hours of electricity access among electrified households are on average approximately equal across caste groups.

Interestingly, though, we see average household expenditure to be a strong and robust predictor of the hours of available electricity. This result can be interpreted in two ways. On the one hand, wealthier communities might have less difficulty paying for electricity, so that they can enjoy more hours per day on average. On the other hand, low-quality electricity service at the village level could prevent households from reaping economic benefits from access to electric power, as the lack of sufficient hours and reliability reduce the economic value of electricity service in the village. This result thus supports the interpretation that the quality of electricity supply is important for socio-economic development from rural electrification.

In Section S5 of the Supporting information, we perform a series of robustness checks by excluding each of the six states in the analysis, one-by-one. These analyses show that the results are not driven by any particular state, as the coefficients show limited variation across the six samples. On the other hand, an analysis of individual states in Section S6 of the Supporting Information shows that, in West Bengal and Madhya Pradesh, caste inequality has disappeared between 2011 and 2014. Given the two states' rapid progress in rural electrification during that time (household electricity access in the average village reached 93% and 83%, respectively) and rural societies that are less caste-centered than those of the other states in the sample (e.g., Lieten (1996); Lieten and Srivastava (1999); Deshpande (2001)), these results are not surprising.

Table 3 extends our analysis of electricity access to households.[7] The unit is a household and the explanatory variables are household expenditure (logarithmized) and caste groups. We estimate logistic regressions with conditional fixed effects and linear probability models with fixed effects, always at the village level. For the caste groups, the omitted category is consistently scheduled caste households. As the table shows, both household expenditures and caste groups are strong predictors of the probability of household electricity access. In models 4 and 6, for example, the baseline category of schedule caste households is 14–15% points less likely to have an electricity connection, when compared to a general caste household in the same village.[8] The difference does not depend on whether or not we control for household expenditure, suggesting that income is not the only channel through which lower caste households have less access to the electric grid.

[7] Within villages, the number of hours of electricity shows little variation across electrified households. We therefore only extended the household-level analysis to electricity access.

[8] In the logistic regressions, the odds ratios for general caste are 2.49–2.80 times higher relative to scheduled caste. Relative to a sample mean of 66% household electrification rate, these models predict a similar increase in probability of 17–19% points.

**Table 1**
Main results. In regressions 1–2, the dependent variable is extracted from the 2011 census questionnaire and corresponds to the fraction of households using electricity as their main source of lighting. In regressions 3–4, the dependent variable is extracted from the survey of village heads and corresponds to the percentage of electrified households in the village. In regression 5–6, the dependent variable is extracted from the survey of households and corresponds to the percentage of households using electricity as their main source of lighting.

| | (1) Census | (2) Census | (3) Village | (4) Village | (5) Household | (6) Household |
|---|---|---|---|---|---|---|
| Scheduled caste population (log) | 1.341** | 1.444** | | | | |
| | (0.625) | (0.637) | | | | |
| Scheduled tribe population (log) | 0.460 | 0.497 | | | | |
| | (0.659) | (0.653) | | | | |
| Other types of population (log) | 2.431* | 2.609** | | | | |
| | (1.294) | (1.291) | | | | |
| Expenditure (log) | 10.585*** | 12.280*** | 12.122*** | 13.396** | 17.407*** | 19.825*** |
| | (3.490) | (3.996) | (3.964) | (5.162) | (3.298) | (3.771) |
| Distance to nearest city (log) | −3.284*** | −3.277*** | −0.001 | 0.032 | −1.549 | −1.510 |
| | (1.013) | (1.028) | (1.017) | (0.993) | (1.074) | (1.072) |
| Surface area (log) | −5.382*** | −5.108*** | −1.038 | −0.967 | −2.058* | −1.809 |
| | (1.868) | (1.816) | (0.933) | (0.896) | (1.062) | (1.106) |
| Habitation Herfindahl | | 7.039 | | 1.091 | | 4.271 |
| | | (4.292) | | (3.663) | | (4.200) |
| Expenditure Gini | | −8.651 | | −6.819 | | −12.271 |
| | | (9.949) | | (15.555) | | (12.452) |
| Scheduled caste households (log) | | | 0.535 | 0.562 | 0.443 | 0.529 |
| | | | (0.450) | (0.445) | (0.418) | (0.429) |
| Scheduled tribe households (log) | | | −0.611 | −0.602 | −0.615 | −0.572 |
| | | | (0.598) | (0.590) | (0.543) | (0.536) |
| Other backward caste households (log) | | | −0.934 | −0.928 | −0.077 | −0.010 |
| | | | (0.629) | (0.654) | (0.541) | (0.539) |
| Other types of households (log) | | | 0.988** | 0.979** | 1.294*** | 1.286*** |
| | | | (0.466) | (0.476) | (0.464) | (0.470) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.073 | 0.079 | 0.037 | 0.037 | 0.074 | 0.077 |
| Observations | 710 | 709 | 709 | 709 | 709 | 709 |

Note: All models are with robust standard errors clustered by district. Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

**Table 2**
Results with hours of electricity as dependent variable. Both models are linear regressions.

| **Dependent variable: hours of electricity** | (1) | (2) |
|---|---|---|
| Scheduled caste households (log) | 0.201*** | 0.204*** |
| | (0.062) | (0.065) |
| Scheduled tribe households (log) | 0.144** | 0.146** |
| | (0.069) | (0.071) |
| Other backward caste households (log) | 0.148* | 0.151* |
| | (0.075) | (0.076) |
| Other types of households (log) | 0.037 | 0.038 |
| | (0.058) | (0.058) |
| Expenditure (log) | 1.752*** | 1.769*** |
| | (0.551) | (0.620) |
| Distance to nearest city (log) | −0.320** | −0.321** |
| | (0.129) | (0.129) |
| Surface area (log) | −0.064 | −0.056 |
| | (0.156) | (0.151) |
| Habitation Herfindahl | | 0.154 |
| | | (0.514) |
| Expenditure Gini | | −0.065 |
| | | (1.474) |
| District fixed effects | Yes | Yes |
| Clustered SE | Yes | Yes |
| R-squared | 0.062 | 0.063 |
| Observations | 699 | 699 |

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

**Table 3**
Household-level analysis. The dependent variable is a dummy for whether or not the household has access to grid electricity. When standard errors are clustered, they are clustered at the village level. Logistic regressions are estimated with conditional fixed effects at the village level; the number of observations decreases from 8563 to 6563 because the conditional fixed effects exclude villages without variation in the outcome variable.

| | (1) Logit | (2) Linear | (3) Logit | (4) Linear | (5) Logit | (6) Linear |
|---|---|---|---|---|---|---|
| Expenditures (log) | 0.706*** | 0.105*** | | | 0.663*** | 0.097*** |
| | (0.055) | (0.010) | | | (0.056) | (0.010) |
| Scheduled tribe | | | −0.077 | 0.003 | −0.136 | 0.000 |
| | | | (0.144) | (0.025) | (0.146) | (0.025) |
| Other backward caste | | | 0.502*** | 0.083*** | 0.455*** | 0.078*** |
| | | | (0.085) | (0.016) | (0.087) | (0.016) |
| Other general caste | | | 1.029*** | 0.152*** | 0.911*** | 0.135*** |
| | | | (0.103) | (0.018) | (0.105) | (0.018) |
| Village fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | No | Yes | No | Yes | No | Yes |
| R-squared | | 0.022 | | 0.016 | | 0.034 |
| Observations | 6563 | 8563 | 6563 | 8563 | 6563 | 8563 |

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

## 4. Targeting and benefits of India's rural electrification program

We next investigate the targeting of villages under the RGGVY and how program implementation correlates with actual improvements in electricity access. In the 2014 village survey, a dummy variable records

**Table 4**
RGGVY targeting. In all models, the dependent variable is the variable 'RGGVY', which is a dummy that equals 1 if the village received RGGVY in the past 3 years. In regressions 7–8, the independent variable is a binary variable converted from the electrification rate from the 2011 census questionnaire: 1 if the rate is above the mean of the sample (33.4%), 0 otherwise. Regressions 1–3 estimate OLS, regressions 4–6 logistic regressions, and regressions 7–8 matching models. In regression 7, we matched on the distance to nearest city, the surface area, and state fixed effects. In regression 8, we matched on the distance to nearest city, the surface area, state fixed effects and the scheduled caste population.

| | (1) OLS | (2) OLS | (3) OLS | (4) LOGIT | (5) LOGIT | (6) LOGIT | (7) M | (8) M |
|---|---|---|---|---|---|---|---|---|
| Electrification rate (0–100) | −0.002** | −0.001** | −0.001* | −0.012*** | −0.011** | −0.010** | | |
| | (0.001) | (0.001) | (0.001) | (0.004) | (0.005) | (0.005) | | |
| Distance to nearest city (log) | 0.003 | 0.004 | 0.002 | 0.032 | 0.052 | 0.058 | | |
| | (0.014) | (0.013) | (0.013) | (0.122) | (0.117) | (0.124) | | |
| Surface area (log) | −0.011 | −0.015 | −0.015 | −0.088 | −0.143 | −0.143 | | |
| | (0.017) | (0.021) | (0.020) | (0.127) | (0.154) | (0.156) | | |
| Expenditure (log) | | −0.108** | −0.169*** | | −1.047** | −1.529*** | | |
| | | (0.048) | (0.054) | | (0.416) | (0.444) | | |
| Scheduled caste population (log) | | −0.000 | −0.001 | | 0.016 | 0.019 | | |
| | | (0.011) | (0.011) | | (0.072) | (0.073) | | |
| Scheduled tribe population (log) | | −0.009 | −0.009 | | −0.050 | −0.056 | | |
| | | (0.008) | (0.008) | | (0.053) | (0.053) | | |
| Other types of population (log) | | 0.016 | 0.018 | | 0.126 | 0.136 | | |
| | | (0.020) | (0.020) | | (0.131) | (0.133) | | |
| Habitation Herfindahl | | | 0.011 | | | 0.086 | | |
| | | | (0.061) | | | (0.466) | | |
| Expenditure Gini | | | 0.441*** | | | 3.502*** | | |
| | | | (0.163) | | | (1.270) | | |
| Electrification rate (binary) | | | | | | | −0.079** | −0.105** |
| | | | | | | | (0.037) | (0.047) |
| State fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | No | No |
| Clustered SE | Yes | Yes | Yes | Yes | Yes | Yes | No | No |
| R-squared | 0.160 | 0.167 | 0.174 | | | | 0.009 | 0.020 |
| Observations | 710 | 710 | 709 | 710 | 710 | 709 | 499 | 253 |

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

whether a village has ever implemented RGGVY and another variable indicates how many years ago the RGGVY started in that village. We are interested in whether a village received RGGVY between the 2011 census and the 2014 surveys, and for that purpose we create a 'RGGVY' indicator: a dummy variable which scores 1 if the village was under RGGVY between the census and the original survey, and 0 otherwise. In our sample, 139 villages were affected by RGGVY during the time period.

To investigate whether RGGVY has targeted villages with low electrification rate, we test if our RGGVY indicator is negatively correlated with a village electrification rate in 2011 census, holding other factors constant. Indeed we observe the state of electrification in 2011 (using census data) and which villages received RGGVY between 2011 and 2014 (using the survey data): with this information, we can check which of the villages in our sample were selected in RGGVY, and in particular whether these villages were some of the poorest ones.

For this analysis, we employ both ordinary least squares (OLS) and logistic regressions (LOGIT). When the dependent variable is binary (0 or 1), logistic regressions are useful because they are based on a plausible functional form of the probability function underlying the outcome. Liner models, however, also perform well when the probabilities that are modeled are not extreme, such that typical probabilities fall on the 20–80% interval, rather than close to 0% or 100%. What is more, the OLS coefficients are easy to interpret, as they represent the estimated change in the probability of a positive outcome when the value of the explanatory variable increases by one. In our case, the mean value of the RGGVY outcome variable is about 0.20, indicating that an OLS regression should be appropriate. We nonetheless show results obtained with logistic regressions for the sake of completeness and statistical rigor. These results are shown in the first six models of Table 4. In the first OLS and logistic regressions, we use basic controls; in the remaining OLS and logistic regressions, we add more socio-economic controls, including scheduled caste population, scheduled tribe population, and other types of population.

For robustness, we also use coarsened exact matching (M) to examine whether villages that in 2011 had higher than average levels of electrification were less likely to benefit from RGGVY implementation. In the matching approach, the effect of a variable – in this case, prior electricity access – is estimated by constructing 'control' and 'treatment' groups that are as similar as possible with regard to observable indicators. Thus, matching produces a sample in which the RGGVY villages are similar to the non-RGGVY villages by construct. To this end, we first transform the electrification rate from the 2011 census (a continuous variable from 0% to 100%) into a binary variable that equals 1 if the 2011 electrification rate is above average of the sample (33.4%), and 0 otherwise. We use this binary variable as a 'treatment' variable. We then implement a matching algorithm to match villages according to various village-level characteristics. We match on two different sets of characteristics, and the results are shown in Columns 7 and 8 of Table 4. In Column 7, we match on the distance to nearest city, the surface area, and the state fixed effects; the matched sample size is 499. In Column 8, we match on the same previous variables, as well as on scheduled caste population, for a matched sample size of 253.[9]

In the six OLS and logistic regressions, the coefficient estimates of the electrification rate, the key independent variable of interest, are all negative and significant, indicating that the lower a village's electrification rate is in 2011, the higher the chances that it will receive RGGVY in the following three years. The coefficient estimates from models 1–3 indicate that an increase of 10% points in electrification rate would on average decrease the probability of receiving the RGGVY by between 1.2% and 1.6% points. In the columns for the matching procedures, which we present for robustness, the coefficient estimates of the binary electrification rate variable are also significantly negative, implying that

[9] For details of the matching procedure and balance statistics, see Section S3-S4.

**Table 5**
RGGVY effects. In regressions 1/3/5/7, the dependent variable is the change (percentage points) in electrification rate between the 2014 village survey and the 2011 census. In regressions 2/4/6/8, the dependent variable is the change (percentage points) between the electrification rate in the 2014 household survey and the 2011 census. Regressions 5–8 use matching. In regressions 5–6, the control and treatment groups are matched on distance to nearest city, surface area and state fixed effect. In regressions 7–8, the control and treatment groups are matched on distance to nearest city, surface area, state fixed effect and scheduled caste population.

| | (1) HH | (2) V | (3) HH | (4) V | (5) HH | (6) V | (7) HH | (8) V |
|---|---|---|---|---|---|---|---|---|
| RGGVY | 10.117*** | 10.610*** | 5.336 | 6.419 | 7.823** | 10.089*** | 7.301 | 9.265* |
| | (3.108) | (3.571) | (3.461) | (3.957) | (3.402) | (3.621) | (4.659) | (5.013) |
| Other types of population (log) | 0.595 | −0.532 | −1.268 | −1.915 | | | | |
| | (1.274) | (1.424) | (1.334) | (1.389) | | | | |
| Scheduled caste population (log) | −0.244 | 0.102 | −0.408 | −0.085 | | | | |
| | (0.835) | (0.969) | (0.834) | (1.062) | | | | |
| Scheduled tribe population (log) | −0.073 | −0.389 | −0.117 | −0.232 | | | | |
| | (0.653) | (0.876) | (0.574) | (0.776) | | | | |
| Expenditure (log) | 8.801* | 10.641* | 10.151** | 10.582* | | | | |
| | (4.514) | (5.529) | (4.383) | (5.276) | | | | |
| Distance to nearest city (log) | 3.597** | 4.601** | 1.956 | 3.339** | | | | |
| | (1.705) | (1.748) | (1.473) | (1.471) | | | | |
| Surface area (log) | −1.915 | 0.459 | 0.686 | 1.656 | | | | |
| | (1.798) | (2.125) | (2.074) | (2.260) | | | | |
| State fixed effects | No | No | Yes | Yes | No | No | No | No |
| Clustered SE | Yes | Yes | Yes | Yes | No | No | No | No |
| R-squared | 0.041 | 0.042 | 0.107 | 0.080 | 0.014 | 0.020 | 0.016 | 0.022 |
| Observations | 710 | 709 | 710 | 709 | 383 | 383 | 152 | 152 |

Note: HH denotes that the improvement in electricity access is measured by the difference between the 2014 *household* survey and the 2011 census, while V denotes that the improvement in electricity access is measured by the difference between the 2014 *village* survey and the 2011 census. Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

having above-average electrification rate decreases the probability of receiving RGGVY by 8–11% points. The results are virtually unchanged if the median (26.4%) is used instead (Table S7). These results indicate that the RGGVY policy did indeed, to some extent, target villages with the lowest electrification rate. As for the control variables, we see that RGGVY targets poor villages and, perhaps surprisingly, those with high levels of inequality. The latter result could reflect the targeting of the lowest quantiles of the expenditure distribution in villages, suggesting a pro-poor policy goal. At the same time, villages with lower caste households do not appear to receive preferential treatment.

Aside from the targeting accuracy of the RGGVY policy, we are also interested in how the RGGVY variable correlates with actual improvements in electricity access. We use the difference between the electrification rates measured in the 2014 survey and measured in the 2011 census to obtain an indicator of improvement in electricity access between 2011 and 2014. If a village has higher electrification rate in 2014 as measured by the surveys, the difference is positive. If a village's electrification rate decreased from 2011 to 2014, this difference is negative. In four OLS regressions, we use the improvement in electricity access as the outcome variable and our RGGVY indicator as the independent variable. We also check the robustness of the OLS regressions using four matching estimations. The results of the eight regressions are shown in Table 5.

The coefficient estimates of RGGVY is significantly positive in models 1–2. These coefficients indicate that having the RGGVY policy between 2011 and 2014 has on average improved electricity access of a village by around 10%. The precision of this positive coefficient is weaker in regressions 3–4, which use state fixed effects, but the coefficients remain positive. The weakening of the estimated RGGVY association with improvement in electricity access suggests that the RGGVY has had some success in reducing inequality in electricity access across states.

The last four regressions in Table 5 use matched samples (see Section S3 of Supporting information for details). In models 5–6, the control and treatment groups are matched on distance to nearest city, surface area and state fixed effects, giving us a matched sample size of 383. In models 7–8, the control and treatment groups are matched on distance to nearest city, surface area, state fixed effects, and scheduled caste population, giving us a matched sample size of 152. The coefficient estimates from the four matching estimations are all positive and about the same size as in the OLS regressions. All but one are significant at the 10% confidence level. This result lends more support to the claim that RGGVY has had a significant and positive impact on electricity access improvement between 2011 and 2014.

Given that India's rural electrification drive focused on providing connections, instead of improving supply, replicating the previous results with number of hours of electricity as outcome variable can be considered as a placebo test. Results are shown in column 3–6 of Table 2 and show that the coefficient on RGGVY is not significant when state fixed effects are included and in the two matching procedures.

## 5. Conclusion and policy implications

India's rural electricity access has improved rapidly over the past decade. By combining data from the 2011 census of India and an original survey fielded during the years 2014–2015, we have investigated changes in India's rural electricity access during the implementation of an ambitious national electrification program. The results show that village land area and distance to the nearest town are no longer powerful predictors of electricity access at the village level. At the same time, wealth and caste inequalities between villages remain stark. Poor villages populated by scheduled castes continue to suffer from low levels of electricity access relative to wealthier villages populated by upper-caste households. The results also hold within villages, as lower caste households have 14–15% points lower electricity access rates than general caste households, regardless of whether we control for household expenditure or not. The evidence also shows that the implementation of the national electrification program, RGGVY, has both (i) appropriately targeted to villages with low previous electrification rates and (ii) associated with rapid improvements in electricity access.

In the light of these findings, we can derive some policy implications for India's rural electrification drive. The gap between the program's success in reducing spatial versus socio-economic inequalities suggests that, if India's goal is universal electrification, the next critical step is to move away from village electrification and focus on electrifying the poorer and lower-caste households. While the RGGVY contained provisions for prioritizing poor households, wealth remains an important predictor of basic electricity access. One reason could be that, in villages populated by poor households, people are unable to afford the monthly electricity bills, and thus have chosen not to take the free connections offered under the RGGVY. Even controlling for average village wealth, caste composition also appears to play a role. An increase in the number of upper caste households contributes consistently to a higher electricity access both in the census and in the original survey data, but adding lower caste households to the village population does not. These findings suggest that policy efforts toward universal electrification should now move from electrifying *villages* to offering affordable electricity connections to poorer and socially disadvantaged *households* within villages. Such measures could make a notable difference to the lives of the households that need improved connections the most, especially if the quality of the electricity service can also be improved. For scholars of energy access, our findings suggest the importance of a renewed emphasis on understanding the socio-economic determinants of electricity access – a topic that has been largely neglected, as most of the literature has focused on quantifying the benefits of rural electrification.

Another important finding of the study pertains to the respective roles of grid extension and off-grid electrification. Between the 2011 census and the 2014–2015 survey analysis, the predictive powers of both distance and village land area for electricity access have diminished. While these results do not mean that off-grid electrification will not play an increasingly important role in the future, they do suggest that some of the skepticism about grid extension as a strategy of rural electrification is unwarranted. The Indian government has, within a short period of time, managed to reduce spatial inequalities in rural electricity access. If the focus of future rural electrification efforts is on poor and socially disadvantaged households within villages that are already linked to the national grid, there is no obvious reason why off-grid solutions would be given particular priority.

## Appendix A. Data and methods

**Representative survey of energy access**. The original survey was done in a collaboration with the Council on Energy, Environment and Water (CEEW), a research institute based in New Delhi, India. 8568 households were surveyed in 714 villages in 51 districts of the following six states: Bihar, Jharkhand, Madhya Pradesh, Odisha, Uttar Pradesh, and West Bengal. Districts were sampled within administrative divisions based on the number of households in them, as per Census 2011. Within each district, seven small and seven large villages were sampled, again proportional to their population sizes. The village groups were formed by splitting the district population into two halves, with 50% of households living in larger villages and 50% of households living in smaller villages. Within each village, a 45-min survey was conducted with 12 households by experienced enumerators from the survey company MORSEL India in a local language (Hindi, Bangla, or Odiya); a 30-min village-level survey was conducted with a village leader such as the *gram panchayat* chairperson or an elder. See Section S1 in the Supporting information for details.

**Variables from original survey**. The original survey was composed of a household survey, for which household heads were interviewed, and a village survey, for which village leaders were interviewed. Through the village survey, an estimate of the percentage of households with electricity access was obtained from the village leader. The household survey provided another estimate based on the answer of individual households which were aggregated to obtain a village-level measure. The household surveys also allowed us to measure average monthly household expenditures within each village and derive an estimate of the gini coefficient for income inequality within the village. The village and household surveys also provided estimates of the number households belonging to the different caste groups: scheduled caste, scheduled tribe, other backward caste, and general. Finally, we counted the number of habitations, as defined by the villagers themselves, and constructed a Herfindahl index for the distribution of population across the habitations, with higher values indicating higher concentration.

**Variables from census of India 2011**. Our main variable of interest, electricity access, corresponds in the census to the fraction of households using electricity as their main source of lighting. Besides electricity access rate, the Census of India 2011 provides a number of useful variables at the village level. While the publicly available census datasets do not provide information about number of households belonging to different caste groups, they do provide information about the number of people belonging to scheduled caste and scheduled tribe groups. We use the logarithmized numbers of people belonging to these different groups as explanatory variables.

The census also contains information on the distance to the closest town (kilometers). At the time we conducted the data analysis, this variable was not available for West Bengal, so we instead used data from the 2001 census for West Bengal. We also recorded the land area (hectares) of the village. Both variables were logarithmized to meet normality requirements for linear regression.

**Dependent variables**. In Table 1, the outcome variable is household electricity access within a village (%). The variable ranges from 0 to 100. When Census 2011 data are used, the variable value is measured in 2011; when original survey data are used, the variable value is measured in 2014. The Census 2011 definition of household electricity access is the use of grid electricity as the primary lighting fuel. The question from the household survey is phrased as follows:

> "Do you use grid electricity for lighting?"Note that the question includes both legal and illegal electricity connections. Because the interviews were conducted at home, the enumerator was also able to easily verify that the respondent gave the correct answer simply by observing the electricity wire. Therefore, the survey design minimizes the risk of incorrect responses. This design feature helps in dealing with the possibility that respondents try to hide illegal electricity connections. The village survey variable is constructed from the village head's estimate of the number of electrified households in the village and the total number of households. Given this measurement, the easiest comparisons are between the census and household survey measures.

In Table 2, the outcome variable is the average number of hours of electricity per day supplied to household, conditional on having access to electricity. The data are from the household survey and the variable spans 0–24 h.

In Table 4, the outcome variable is the probability of RGGVY implementation between 2011 and 2014. The data are from the village survey. For each village, we have a binary indicator for RGGVY implementation during the period of investigation. Because RGGVY implementation is absent from many districts, we use state fixed effects to avoid losing variation.

In Table 5, the outcome variable is the change in household electricity access within a village (%) between 2011 and 2014. The 2011 data are from Census 2011; the 2014 data are from the original survey.

**Statistical methods: village electricity access**. Our primary statistical methods are linear fixed effects regressions and coarsened exact matching. In the linear regressions, the outcome variable is either electricity access (%) or change therein (percentage points). In the models of RGGVY implementation, we also estimate logistic regressions to account for the probability distribution. In the models at the household level in Table 3, we estimate both OLS regressions (village fixed effects) and logistic regressions (conditional village fixed effects). The primary specifications in Table 1 can be written as follows:

$$Y_{i,j} = \alpha_j + \sum_k \beta_k x_{i,j}^k + \epsilon_{i,j}, \tag{1}$$

where villages $i$ are grouped under districts $j$, so that $\alpha_j$ is the district fixed effect. In turn, $\beta_k$ is the coefficient for explanatory variable $x_{i,j}^k$ and $\epsilon_{i,j}$ is the error term. The dependent variable $Y_{i,j}$ is the village electricity access rate (0–100). Robust standard errors are clustered by district except in Table 3, for which we cluster robust standard errors at the village level. For explanatory variables $x_{i,j}^k$, see Table 1.

## Appendix B. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org.10.1016/j.enpol.2017.03.048.
A replication package can be found on Harvard Dataverse at http://dx.doi.org/10.7910/DVN/K1IUNQ.

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