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Early electrification and the quality of service: Evidence from rural India☆

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ABSTRACT

Rural electrification has progressed unevenly across the world since 1945, with some rural communities gaining access to power decades earlier than others. We examine the association between early electrification and the quality of electricity service to households, testing the hypothesis that aging infrastructure compromises the quality of electricity service. Using the 2014–2015 ACCESS survey from rural India, we find that early electrification is associated with improvements in the quality of electricity service, even controlling for village size and distance to nearest town. A possible explanation for the finding is that early electrification generates economic gains that allow the rural community to invest in maintenance and upgrades.

Introduction

Rural electrification has progressed across the developing world over the past decades, with rural electrification at the global level reaching 84% by 2014 (IEA, 2016). One important consequence of the considerable variation in the time of electrification is that the equipment used varies across locations. In areas that were electrified early, the core electricity distribution infrastructure can be decades old and, depending on the country, sometimes of Soviet origin. In more recently electrified areas, the equipment can be more modern and recent.

In our recent fieldwork in the state of Uttar Pradesh in India, we saw this dynamic in action. In Hardoi district, where many villages had been electrified 3–4 decades ago, villagers complained about very low hours of supply. They noted that the infrastructure had fallen into disrepair and that even on those days when the electricity substations received over twelve hours of supply, many villages received only a fraction of this theoretical maximum.

In most respects, early electrification is good for communities. Translating energy access into economic gains takes time, so communities that were electrified early have an economic advantage over communities that were electrified in more recent years. At the same time, however, early electrification means dependence on infrastructure that is by now outdated. If communities that were electrified early have not benefited from regular maintenance, it is possible that the quality of their electricity service is actually worse than that of more recently electrified communities. What is more, such maintenance problems are widespread given that electricity distribution companies in most developing societies have been in serious financial trouble for decades (Victor & Heller, 2007; Urpelainen & Yang, 2017).

As a first step toward assessing the possible disadvantages of early electrification, here we use data from villages in six energy-poor states of India. Drawing on the ACCESS data (Jain et al., 2015; Aklin, Cheng, Ganesan, Jain, Urpelainen, & Council on Energy, Environment and Water, 2016; Aklin, Cheng, Urpelainen, Ganesan, & Jain, 2016) for 594 electrified villages, we assess the relationship between the time of electrification and the household electrification rate, daily hours of electricity available, and monthly days without electricity. While it is intuitive that early electrification should boost household electrification rates, the association between the time of electrification and the quality of service (more hours, fewer outages) could be either negative or positive.

We find that early electrification has been unambiguously beneficial to the villages in the sample. Not only electrification rates, but also hours of supply increase with early electrification. Similarly, outages are less frequent in villages that were electrified early. These results hold even if we control for distance to nearest town and include district fixed effects ($N = 51$), so that the finding cannot be attributed to transmission distance, variation in geography, or other factors.

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These results suggest that on balance, early electrification has been a boon to the villages benefiting from it. Although early electrification means that the original infrastructure is inferior to what would be used today, in practice the net effect is positive. Thus, our results add new insights into the increasingly important issue of variation in the quality of electricity supply (e.g., Chakravorty, Pelli, & Marchand, 2014; McRae, 2015; Aklin, et al., 2016). We identify the timing of electrification as a critical issue, and thus confirm the importance of understanding why some areas of different countries were historically electrified early and others were not (e.g., Samanta & Sundaram, 1983; Rud, 2012; Kale, 2014).

The results also suggest possibly important insights into the relationship between rural electrification and economic development. The primary reason why early electrification is good for rural communities is that access to power enables livelihood activities such as groundwater irrigation and rural industry. Though much additional research is needed, our findings suggest that these economic benefits might generate a virtuous cycle, whereby early electrification enables rural communities to invest in maintaining the electricity infrastructure and thus continue benefiting from adequate service. Indeed, to the extent rural communities use electricity for economic activity, the incentive to maintain infrastructure is strong and direct.

Quality of rural electricity service

Quality of rural electricity service remains a major issue around the world. Outages, voltage fluctuation, and restricted hours of supply reduce the value of an electricity connection at home. In the ACCESS survey that we use, for example, the average grid-electrified household only receives about 13 hours of supply on a typical day and had almost four outage days per month. This low quality of rural electricity service, in turn, is robustly associated with households' dissatisfaction with electricity service (Aklin, et al., 2016). Other studies report that the lack of reliability discourages households from connecting to the grid (Millien, 2017) and impedes the productive use of power (Chakravorty et al., 2014).

Electrification, and quality of service in particular, can have substantial effects on economic outcomes for firms and households. At the firm level, Alby, Dethier, and Straub (2012) demonstrate that poor quality of service in the form of outages can skew the industrial structure toward large firms in sectors that rely heavily on electricity. In a study specific to India, Allcott, Collard-Wexler, and O'Connell (2016) show that shortages increase input costs for plants in the short run, although the effect is not large. Moreover, in the long run, plants are less likely to entry electricity-intensive industries when shortages worsen. Using simulations, they also show that shortages reduce producer surplus, revenues and productivity for the average plant. Similarly, Rud (2012) uses an instrumental variables design to show that increasing electrification has positive effects on manufacturing output across Indian states.

The quality of electrical service also has impacts on household outcomes. Dinkelman (2011) shows that rural electrification has a positive impact on female employment. Peters and Vance (2011) demonstrate that electrification has a negative effect on fertility for rural households. In the context of Vietnam, Khandker, Barnes, and Samad (2013) compare villages that adopted electricity at different times in order to examine the welfare impacts of rural electrification. They find that household electrification increases total income, expenditure and children's school attendance. Because it is well established in the literature that the quality of service of electricity has impacts on firms and households, it is important to understand the determinants of service quality.

Few studies in the past have considered the impact of the timing of electrification on any outcome variables, and even fewer have considered the impact on the performance of electrical infrastructure. Many studies cite age as a factor contributing to the deterioration of electrical infrastructure, but do not specifically test this argument (Brown & Willis, 2006; Utazi & Ujam, 2014; Li & Guo, 2006). Other studies examine the microfoundations of aging electrical infrastructures. Datla and Pandey argue that the aging of wood poles can lead to pole failure, leading to electrical outages and the need for maintenance (Datla & Pandey, 2006). Similarly, in the context of wind farms, Staffell and Green (2014) find that age has a negative effect on wind turbine performance.

In a study with similar outcome measures to ours, Sultan, Alzahrani, Bitar, and Alharbi (2016) ask whether power outages in California can be attributed to aging infrastructure. They find that the age of power plants has no effect on the prevalence of power outages. Similarly, Barnes and Binswanger examine the impact of the age since electrification in Indian villages on agricultural outcomes, and find that early electrification had a positive impact on the development of agricultural infrastructure, including investment in pumps, multiple cropping and agricultural innovations (Barnes & Binswanger, 1986). However, to our knowledge, no study has explicitly examined the effects of early electrification on the efficacy of electrical infrastructure in India.

History of rural electrification in India

When India became an independent nation in 1974, rural electrification was minimal, with only 0.6% of all villages electrified (Samanta & Sundaram, 1983). Electrification was largely restricted to urban areas. While growth in rural electrification was slow for the first two decades, the beginning of India's "green revolution" resulted in rapid rural electrification as the introduction of high-yielding varieties to agriculture massively increased demand for groundwater and electric pumps were used to extract it from the ground (Kale, 2014; Rud, 2012). Despite this expansion in rural electrification, the 1981 Census of India recorded only a 15% household electrification rate in rural areas.

After the 1991 liberalizing reforms, India's rural electrification rates have grown rapidly, and yet in the 2011 Census of India, the rural electrification rate remained at 55%. The main reason why almost one-half of rural India remained without electricity access is that electrification rates in the large, Hindi-speaking states of the north, remain very low. Bihar's rural electrification rate at the time was only 10% and Uttar Pradesh's also languished at 24%.

Since 2005, India has invested billions of dollars in a national rural electrification drive. Initiated by Prime Minister Manmohan Singh, the drive was initially named after Rajiv Gandhi, the sixth Prime Minister of India who was assassinated in May 1991, and then re-branded as the Deendayal Upadhyay scheme by Prime Minister Modi after his Bharatiya Janata Party (BJP) won the general elections in May 2014. The scheme, which offers a 90% capital subsidy for states that join for rural electrification projects, had reached 104,496 non-electrified villages and 248,553 poorly electrified villages, with almost 20 million households below India's poverty line electrified.

Although India's rural electrification has progressed over time, the poor quality of electricity supply remains a serious problem in many areas of the country. Outages are frequent, and in July 2012 India had the questionable distinction of the world's largest outage leaving 700 million people in the northern parts of the country in the dark for a day. According to the ACCESS survey, in the six states under investigation the typical village with an electricity connection had on average only twelve hours of supply, and the minimum was as low as one.

The roots of the quality problem can be found in the governance of the power sector (Dubash & Rajan, 2001; Tongia, 2004; Baskaran, Min, & Uppal, 2015). Lacking regulatory autonomy, many Indian electricity distribution companies sell electricity at prices well below the cost of generation, transmission, and distribution. Agricultural and rural prices are particularly low, so that urban and industrial consumers essentially cross-subsidize the consumption (Chattopadhyay, 2004). As a result of this cross-subsidy, distribution companies have few resources to maintain infrastructure in rural areas, let alone an incentive to improve the quality of rural supply: for every unit of power sold, these electricity distribution companies lose money (Harish & Tongia, 2014). In large part because of this artificial pricing system, the quality of rural electricity supply in India is often low.

Research design

Our research design is intended to estimate the association between time since rural electrification and the quality of electricity service, in terms of the electrification rate of villages, daily access to electricity, and monthly electrical outages. To accomplish this, we estimate linear regression models, varying the inclusion of control variables and state and district-level fixed effects[1]. The unit of analysis in our models is the village, restricted to those villages that had access to electricity when the survey was conducted, between November 2014 and May 2015.

In our design, we employ a dataset of 594 villages across 51 districts and 6 states – Madhya Pradesh, Uttar Pradesh, Bihar, Jharkhand, West Bengal, and Odisha – drawn from ACCESS. Districts were sampled randomly within administrative divisions, and villages were selected based on population size (with 50% of the villages being 'large' and the other 50% being 'small'). The 594 villages employed in this study were drawn from an overall sample of 714. A map of the villages and their years since electrification can be seen in Fig. 1.

In our analysis, we estimate the following models:

$$Y_{ijk} = \alpha_{jk} + \beta_1 Years_{ijk} + \beta_n \Phi_{ijk} + \epsilon_{ijk}, \tag{1}$$

where i denotes villages, j districts, and k states. The primary outcome variables of interest Y_{ijk} are either village electrification rate (0–100), daily hours of electricity (0–24), or monthly days of complete blackout (0–30). α is a set of either district or state-level fixed effects that account for any unobserved determinants of the quality of electrical service. $\beta_n \Phi_i jk$ is a set of n control variables, the inclusion of which varies by model. We cluster the standard errors ϵ_{ijk} by district.

Dependent variables

Our analysis has three dependent variables. We begin by estimating the effect of time of electrification on village electrification rate. The variable **Village Electrification Rate** is the percentage of households reported to have access to electricity in a village ($0-100$) at the time the survey was conducted. In the dataset, the variable ranges from a minimum of 8.333% to a maximum of 100%.

Next, we analyze the effect of time of electrification on the mean daily hours of access to electricity in our sample villages. **Daily Hours of Electricity** is the mean daily hours of access to electricity in a village. The variable can fall between $0-24$ and in our sample ranges between 1.000 and 23.083. An increase in daily hours of access to electricity would indicate that early electrification has created stronger electricity infrastructure over time.

Finally, we estimate the effect of time of electrification on mean days without electricity in villages. Like daily access to electricity, **Monthly Outages** proxies for the efficacy of electricity infrastructure. In our sample, the variable ranges from a minimum of 0 outages per month, to a maximum of 25 outages.

The distributions of the three dependent variables are shown in Fig. 2. The distribution of village electrification rate has a spike near 100%, whereas most of the observations of monthly outages are clustered at low levels. The distribution of daily hours of access to electricity is nearly uniform.

Explanatory variable

Our primary explanatory variable is a count of years since the village was first electrified (i.e., distribution lines were drawn and at least one electricity connection included). The first village in the sample was electrified 58 years before the survey, and the last only months before the survey was completed. The histogram of **Years Since Electrification** is shown in Fig. 3.

The association between years since electrification and the three dependent variables is illustrated in Figs. 4 and 5. Box plots show the relationship for observations grouped by years since electrification. Both village electrification rate and daily hours of electricity exhibit a positive linear association with years since electrification, whereas monthly outages of electricity decline as years since electrification increases. These associations all serve as rough indications that early electrification has been a boon for villages.

Control variables and fixed effects

In our analysis, we model the relationship between years since electrifcation and the outcomes while varying the inclusion of control variables and fixed effects. The primary challenge for our estimation, which focuses on associations and does not attempt to estimate causal effects, is to ensure that we control for potential confounders and obtain a good estimate of the correlation between time since electrification and the three dimensions of quality listed above. A multivariable regression can achieve this goal by controlling for variables that could explain both time since electrification and the quality of supply. With these controls, we can isolate the partial association between time and the quality of supply. While this association may or may not be causal, our method should be able to isolate it from other influences. In future research, we hope to move toward an estimate of the causal effect of time since electrification on the quality of supply.

We employ three control variables. The first is **Distance to Town**, which is the logarithm of the distance in kilometers of a village from the nearest town. The variable controls for the ease of electrifying villages closer to pre-existing infrastructure. Historically, distance to town has been a key predictor of rural electrification, as villages close to towns could be electrified at a much lower cost (Kale, 2014). At the same time, distance to town also shapes opportunities for economic activity because of distance to markets and other infrastructure. Thus, controlling for distance to town is a good way to reduce bias and enhance the precision of our estimates.

The second control variable controls for the population of villages in the form of number of households. **Number of Households** is the logarithm of the number of households in a village. The size of a village is another potential determinant of electrification, as large villages have greater economic opportunities and thus benefit more from access to power. Moreover, electrifying large villages directly benefits more households.

The third variable is the percentage of a village's population that is a member of the scheduled Caste or Tribe. **Percent Scheduled Caste/Tribe** controls for the socioeconomic status of the population of villages, as previous research shows that historically lower-caste

[1] Results of a Hauman test indicated that random effects were more efficient than fixed effects at the state level. Therefore, we include state-level random effects estimation in the appendix. The results remain statistically significant and maintain the same sign.

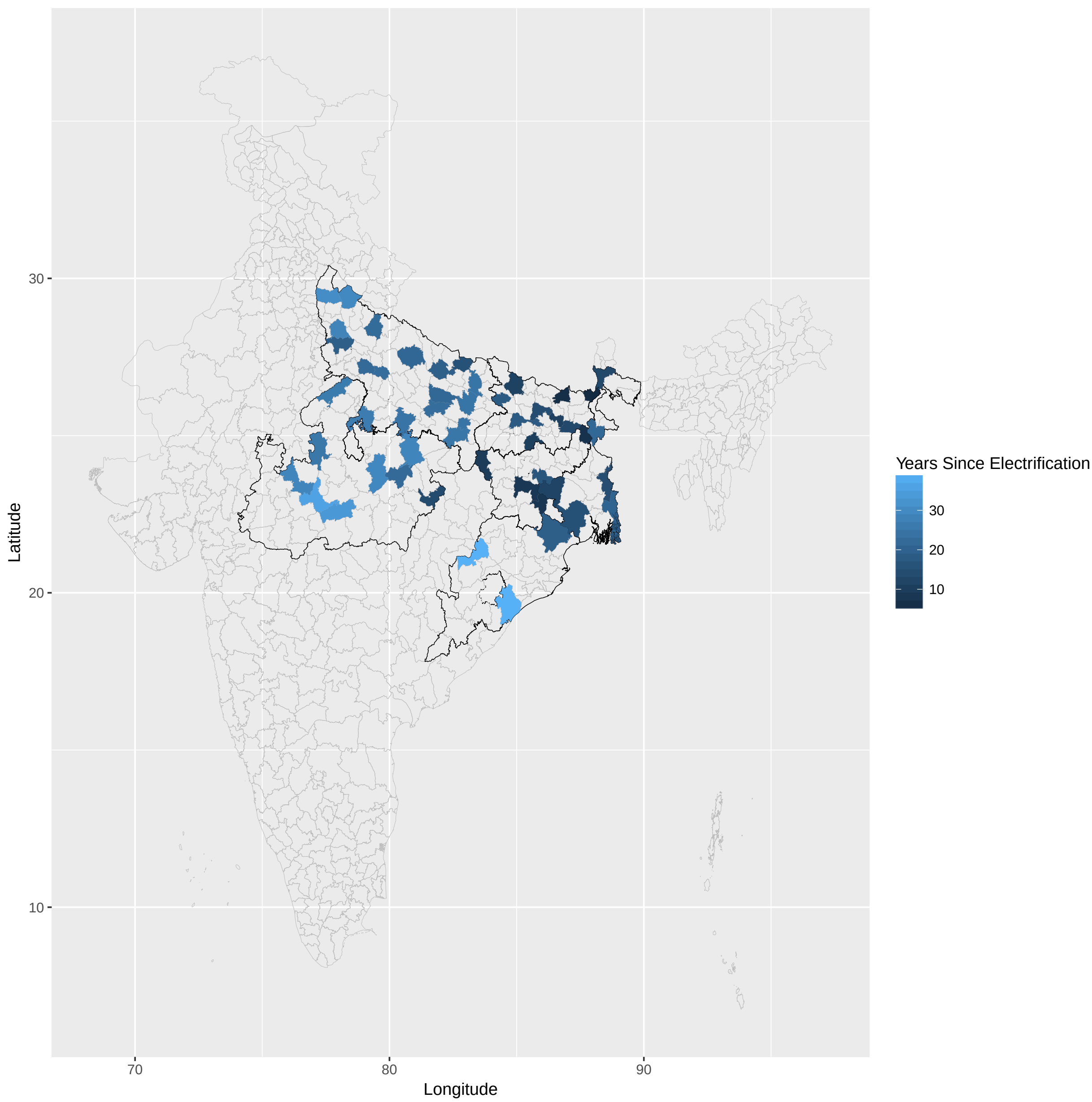

Fig. 1. The district-level average number of years since village electrification. Darker shades indicate less time since village electrification.

communities have fallen behind in rural electrification (Dugoua, Liu, & Urpelainen, 2017). All data for the control variables was acquired from the ACCESS dataset.

We use these variables because they control for aspects of the villages in the sample that are not affected by electrification. Certainly, the introduction of electricity did not alter the distance of villages to major towns, and it is reasonable to assume that the population of villages and their socioeconomic composition was not affected as well.

Along with these control variables, we also vary the use of and type of fixed effects. In some models, we use state fixed effects, controlling for factors unique to the six states in the sample. We then estimate our models with district level fixed effects, controlling for heterogenous factors present in the 51 districts in our sample. We include state and district level fixed effects because policies, geographical conditions and other factors vary between states and districts. Summary statistics for all variables used in the analyses are shown in Table 1.

Missing data

One issue we need to consider before presenting the results is missingness in our dependent variable. The original ACCESS dataset has 714 villages, but of those only 669 had a grid connection at the time of the survey. Furthermore, another 76 villages were missing data on the time of electrification because the village leaders could not recall. While grid-connected villages are the natural unit of analysis, it is useful to see whether our control variables predict missingness of the timing data. We thus estimate regressions with our control variables on a binary indicator for missing data.

The results are reported in Table 2. The models are identical except for the choice of fixed effects. As the table shows, none of our control variables predict missingness. The coefficients are always small and statistically insignificant. This result is consistent with the idea that data on the dependent variable is missing at random, meaning there is no bias from missingness. We similarly expect any measurement error in the dependent variable to be random, as there

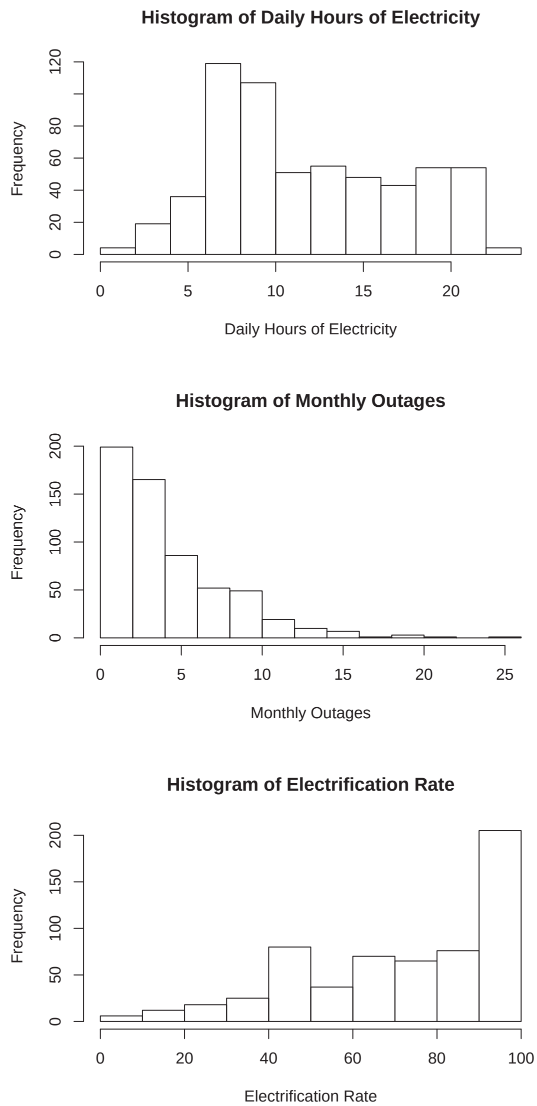

Fig. 2. Distributions of dependent variables.

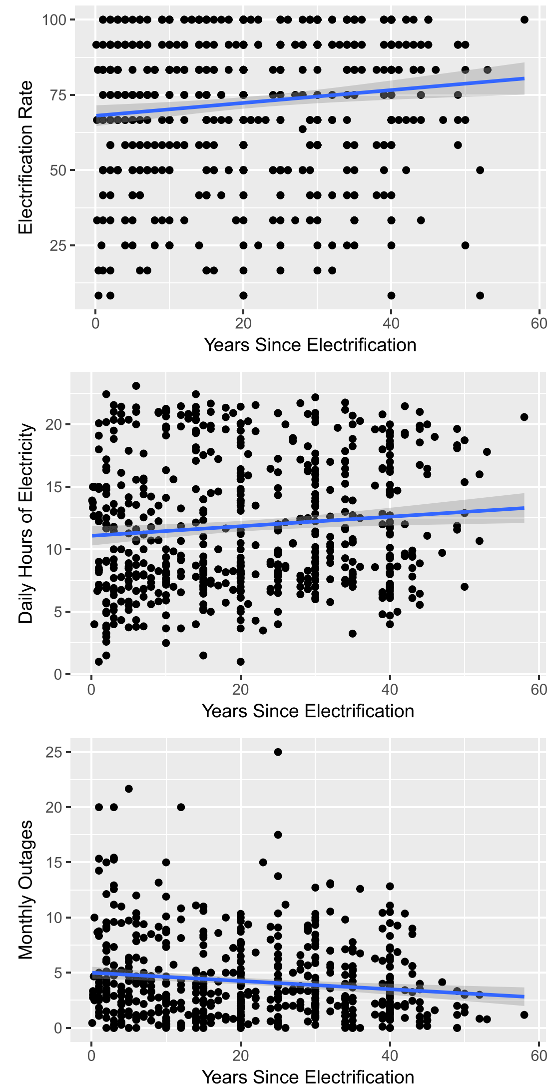

Fig. 4. Scatter plots of explanatory and dependent variables. Fitted lines are determined through linear regression of the form $Y = \beta_1 Years + \epsilon$.

is no reason to believe the respondents would systematically over- or underestimate years since electrification; such random error in the dependent variable does not result in bias but only increases uncertainty around the results.

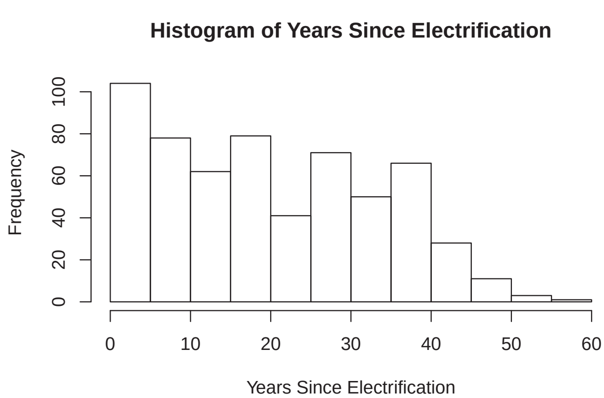

Fig. 3. The distribution of the explanatory variable.

Propensity score weighted regression

To further assess the validity of our results, we utilize propensity score weighted regression. To construct the propensity score weights, we employ the CBPS package in R (Imai & Ratkovic, 2014). Because our main predictor variable, Years, is continuous, we create weights based on the conditional probability of having been electrified for a certain number of years. The purpose of this method is to allow for more precise identification of the effect of the predictor variable on our outcomes by adjusting for observed variables that affect assignment to treatment.

To create the weights, we use the same battery of control variables as in our simple estimations above along with state fixed effects. The use of these variables could be problematic as they were measured in 2015 and thus may have been affected by electrification. A better estimation of propensity scores would use data from before any villages were electrified, but such data is not available. Thus the results of the model assume that the variables predicting treatment are not endogenous to the treatment itself. If this assumption is not true, the results may be biased.

We first present the Pearson correlations between the covariates and the treatment variable for the balanced and unbalanced samples.

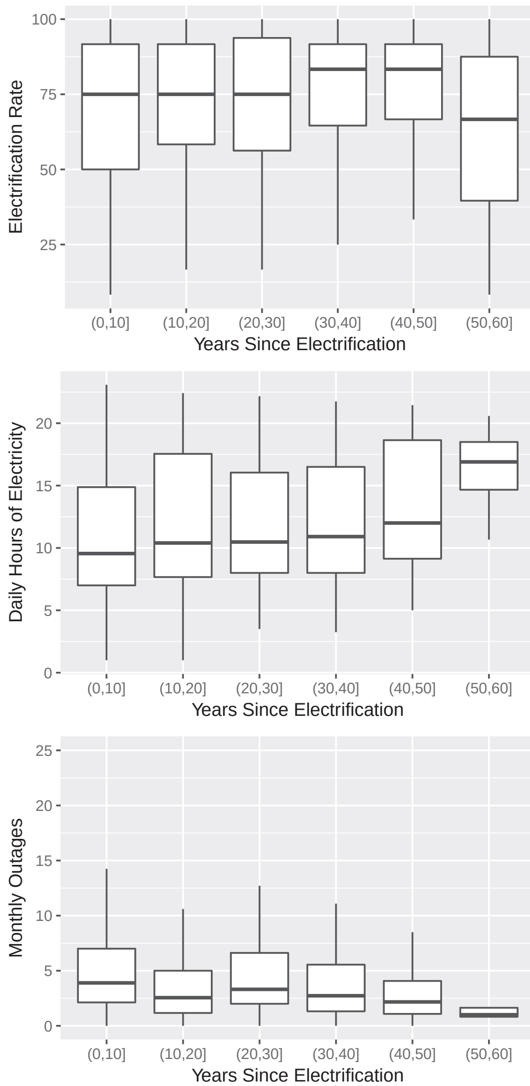

Fig. 5. Box plots of explanatory and dependent variables.

We also check the balance between the covariates and the treatment after using a Box-Cox transformation on the treatment variable to better meet the assumption that the treatment is normally distributed, following the method of (Fong, Hazlett, & Imai, 2017). The transformation takes the form of

$$(Years^{\lambda} - 1)/\lambda$$

where $\lambda = 0.5718459$. The distribution of the transformed variable is displayed in Fig. 6.

Table 1
Summary statistics.

Statistic	N	Mean	St. dev.	Min	Max
Years Since Elec.	594	21.255	13.917	0.100	58.000
Monthly Outages	593	4.202	3.720	0.000	25.000
Daily Hours of Elec.	594	11.889	5.278	1.000	23.083
Village Electrification Rate	594	72.596	23.715	8.333	100.000
Distance to Town	594	17.623	16.309	0	121
Distance to Town (log)	594	2.583	1.275	−2.303	4.701
Number of Households	593	537.209	669.686	35	7000
Number of Households (log)	593	5.868	0.894	3.555	8.854
Percent Scheduled Caste/Tribe	594	26.103	26.641	0.000	100.000

Table 2
Analysis of missing data: logistic regressions of the missingness indicator on control variables and fixed effects.

	Dependent variable:		
	Missingness of years since electrification variable		
	(1)	(2)	(3)
Distance to Town (log)	−0.033	−0.113	−0.164
	(0.123)	(0.123)	(0.161)
Number of Households (log)	0.128	0.170	0.226
	(0.196)	(0.170)	(0.191)
Percent Scheduled Caste/Tribe	−0.006	−0.003	−0.004
	(0.007)	(0.006)	(0.006)
Constant	−2.592**	−3.155***	−3.785***
	(1.180)	(1.081)	(1.330)
State FE?	No	Yes	No
District FE?	No	No	Yes
Observations	669	669	669
Log likelihood	−235.241	−219.667	−177.201
Akaike Inf. Crit.	478.482	457.334	462.403

Standard errors clustered at district level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3 shows these coefficients for the propensity-score weighted regression. Weighting the variables improves the balance for each control variable, although it does not eliminate the imbalance. After transforming the treatment variable, the magnitude of the correlations between the control variables and the treatment variable do not change in a notable or homogenous manner. We proceed by estimating the effect of the transformed treatment variable on the same outcomes as in our previous models. The same models with the untransformed treatment variable are available in the Appendix (Table A1).

Results

We begin by analyzing the effect of years since electrification on village electrification rate. The results of this analysis are available in Table 4. Standard errors are clustered at the district level throughout the analysis to control for intra-district error correlation.

We first estimate models without controls, varying fixed effects. Model 1 reports the relationship between years since electrification and village electrification rate without the inclusion of control variables or fixed effects. The result is strongly positive, indicating that villages that were electrified earlier have higher rates of electrification.

We then vary the inclusion of control variables and the level of fixed effects. The result holds with the inclusion of state-level fixed effects and the full battery of control variables. However, with the

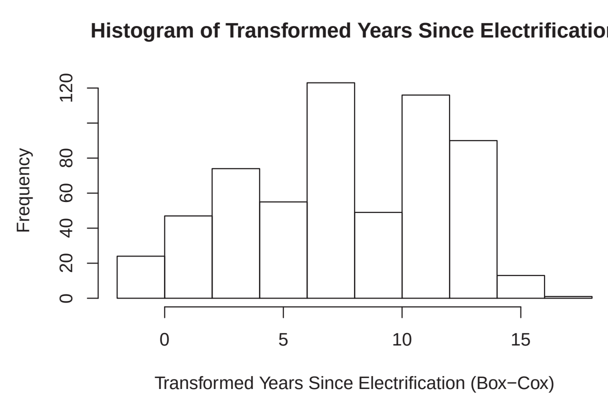

Fig. 6. Histogram of transformed explanatory (treatment) variable.

Table 3
Balance table of coefficients. The cell values show the association between the different control variables and the treatment variable.

	Unweighted	Balanced	Unweighted (Box-Cox)	Balanced (Box-Cox)
Distance to Town (log)	−0.153	−0.087	−0.163	−0.085
Number of Households (log)	0.168	0.121	0.163	0.120
Percent Scheduled Caste/Tribe	−0.066	−0.051	−0.075	−0.052

Table 4
Linear regressions of electrification rate (0–100) on years since electrification, control variables, and fixed effects.

	Dependent variable:					
	Village Electrification Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Years Since Elec.	0.213**	0.210**	0.064	0.247**	0.203**	0.040
	(0.106)	(0.096)	(0.086)	(0.105)	(0.096)	(0.091)
Distance to Town (log)				0.944	−1.016	−1.232
				(1.367)	(1.223)	(1.045)
Number of Households (log)				−1.208	−0.614	0.679
				(1.545)	(1.133)	(0.952)
Percent Scheduled Caste/Tribe				0.096*	−0.019	−0.001
				(0.058)	(0.047)	(0.039)
Constant	68.058***	57.830***	83.306***	69.462***	64.142***	81.719***
	(3.188)	(3.592)	(2.640)	(9.218)	(6.598)	(5.733)
State FE?	No	Yes	No	No	Yes	No
District FE?	No	No	Yes	No	No	Yes
Observations	594	594	594	593	593	593
Adjusted R^2	0.014	0.265	0.442	0.028	0.264	0.441

Standard errors clustered at district level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

inclusion of district-level fixed effects, the coefficient is much smaller and does not reach conventional levels of statistical significance. This indicates that factors unique to districts accounts for much of the variation in village electrification rate.

Next we estimate the effect of years since electrification on the mean daily hours of electricity in villages. The results of this analysis are reported in Table 5. Standard errors are again clustered at the district level.

We once again estimate the relationship without controls or fixed effects, and then vary the inclusion of controls and the level of fixed effects. Without the inclusion of fixed effects, the results do not reach conventional levels of statistical significance. However, once we control for unique factors at either the state or district level, a notable effect is found. Indeed, the coefficients for the years variable across the six models indicate that, at a minimum, an increase in one year since electrification leads to about 0.03–0.04 h of electricity per day. This effect remains significant with the inclusion of the full battery of control variables.

Lastly, we estimate the relationship between monthly electrical outage days and years since electrification, once again varying the inclusion of control variables and fixed effects. The results are presented in Table 6. Again, standard errors are clustered by district.

Table 5
Linear regressions of daily hours of electricity availability (0–24) on years since electrification, control variables, and fixed effects.

	Dependent variable:					
	Daily Hours of Electricity					
	(1)	(2)	(3)	(4)	(5)	(6)
Years Since Elec.	0.038	0.040***	0.036***	0.044	0.042***	0.031***
	(0.029)	(0.012)	(0.010)	(0.027)	(0.013)	(0.009)
Distance to Town (log)				0.278	−0.244**	−0.198**
				(0.220)	(0.116)	(0.095)
Number of Households (log)				0.313	−0.029	0.241
				(0.348)	(0.230)	(0.153)
Percent Scheduled Caste/Tribe				0.053***	0.014**	0.004
				(0.015)	(0.007)	(0.005)
Constant	11.076***	7.882***	6.785***	7.008***	8.288***	5.651***
	(1.029)	(0.793)	(0.293)	(1.991)	(1.849)	(1.093)
State FE?	No	Yes	No	No	Yes	No
District FE?	No	No	Yes	No	No	Yes
Observations	594	594	594	593	593	593
Adjusted R^2	0.009	0.556	0.775	0.077	0.562	0.777

Standard errors clustered at district level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 6
Linear regressions of monthly outage days (0–30) on years since electrification, control variables, and fixed effects.

	Dependent variable:					
	Monthly Outages					
	(1)	(2)	(3)	(4)	(5)	(6)
Years Since Elec.	−0.037***	−0.056***	−0.041***	−0.033***	−0.052***	−0.035***
	(0.014)	(0.015)	(0.013)	(0.013)	(0.013)	(0.012)
Distance to Town (log)				0.096	0.193	0.156
				(0.161)	(0.143)	(0.167)
Number of Households (log)				−0.542**	−0.276	−0.338
				(0.237)	(0.197)	(0.208)
Percent Scheduled Caste/Tribe				−0.024***	−0.013*	−0.009
				(0.009)	(0.007)	(0.006)
Constant	4.996***	6.044***	5.488***	8.455***	7.399***	7.386***
	(0.507)	(0.542)	(0.411)	(1.516)	(1.413)	(1.470)
State FE?	No	Yes	No	No	Yes	No
District FE?	No	No	Yes	No	No	Yes
Observations	593	593	593	592	592	592
Adjusted R^2	0.018	0.176	0.289	0.047	0.184	0.294

Standard errors clustered at district level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Once again, we find evidence that an increase in years since electrification improves the efficacy of villages' electrical infrastructure. Across all models, the effect is strong and statistically significant. An increase in one year since electrification decreases the number of monthly electrical outages by 0.033 according to the lowest estimate in our models.

Robustness: propensity score weighted regression

Table 7 displays the results of the propensity-score weighted regressions with the transformed predictor variable. The results are consistent with the models presented earlier, although the relationships are slightly less significant or do not retain their statistical significance. Of note, the relationship between years since electrification and village electrification rate loses its significance with the propensity weights included and without state fixed effects or control variables. The relationship between years since electrification and monthly outages also loses its significance without the inclusion of fixed effects. However, all relationships are in the same direction as in our earlier models, lending credibility to their results.

Robustness: interaction terms

As a step toward determining the mechanisms underlying our results, we include models with interactions between the Years Since Electrification variable and the control variables. These results are available in the Appendix. This approach is intended to determine whether the relationship between Years Since Electrification and our outcome variables depends on the value of the control variables. However, this approach does not allow us much insight into the mechanisms as the results largely are not statistically significant. We do observe some one broad trend. As distance from towns increases, the effect of increasing the number of years since electrification on our outcomes diminishes, except in the case of Monthly Outages, where the effect increases along with distance.

Conclusion

Rural electrification has expanded only slowly over time, with countries such as India still far from the goal after seven decades of programs and policies. One important consequence of this slow progress is that different rural communities have been electrified at very different times. Among the electrified villages in the ACCESS sample, for example, some villages were electrified as early as in 1956 while others had been electrified only months before the survey, in the fall of 2014. Here we have assessed the association between early electrification and the quality of electricity service. We have found that villages electrified early still enjoy better quality of service than those electrified recently, a result that holds after controlling for confounders such as village size and distance to nearest town.

Our findings suggest that simply electrifying villages is insufficient for providing quality electrical service. Although increasing the electrification rate is important, greater attention needs to be paid to ensuring that newly electrified villages benefit from high quality service. We show that despite greater electrification rates in India, a gap still exists between villages that have been electrified recently and those electrified in the past. To close this gaps, policymakers should strive to provide newly electrified villages with the infrastructure necessary to match the quality of service present in villages electrified in the past.

While this correlational evidence should be interpreted with caution, it does offer motivation for additional studies. Given that early electrification is unambiguously positive for the quality of electricity service, the next natural questions concern the reasons behind this positive result. Has aging infrastructure not compromised the quality of electricity supply? Or, have the electrified communities invested heavily in maintenance and repairs? Our data cannot answer these questions, but they are important for understanding whether aging electricity infrastructure could cause serious problems in the future. If the first communities to be electrified are those with the best opportunities for productive uses of power, then the future might bring about less positive outcomes, as rural communities with fewer growth opportunities are electrified and may lack the economic self-interest and resources to invest in infrastructure maintenance.

More generally, our study calls for renewed attention to the quality of electricity service. As rural electrification rates increase across the world, the next frontier for energy access policy is to ensure that electricity connections – whether grid or off-grid – can provide the kind of power that contributes to livelihoods and daily life. The examination of the determinants of the quality of access to power offers exciting opportunities for social scientists, engineers, and other researchers to contribute to the quest for universal energy access.

Table 7
Propensity score weighted regressions of electrification rate, daily hours, and monthly outages.

	Dependent variable: Village Electrification Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Years Since Elec.	0.657	0.774**	0.277	0.777*	0.778**	0.225
	(0.418)	(0.337)	(0.300)	(0.414)	(0.332)	(0.315)
Distance to Town (log)				1.381	−0.803	−1.104
				(1.490)	(1.329)	(1.140)
Number of Households (log)				−0.819	−0.545	0.416
				(1.538)	(1.075)	(0.957)
Percent Scheduled Caste/Tribe				0.113**	−0.013	−0.012
				(0.055)	(0.040)	(0.036)
	Dependent variable: Daily Hours of Electricity					
	(1)	(2)	(3)	(4)	(5)	(6)
Years Since Elec.	0.094	0.128***	0.124***	0.120	0.146***	0.114***
	(0.113)	(0.046)	(0.034)	(0.101)	(0.046)	(0.032)
Distance to Town (log)				0.409*	−0.132	−0.086
				(0.224)	(0.114)	(0.087)
Number of Households (log)				0.427	−0.062	0.199
				(0.355)	(0.243)	(0.152)
Percent Scheduled Caste/Tribe				0.062***	0.018***	0.006
				(0.016)	(0.007)	(0.005)
	Dependent variable: Monthly Outages					
	(1)	(2)	(3)	(4)	(5)	(6)
Years Since Elec.	−0.075	−0.148***	−0.109**	−0.070	−0.147***	−0.098*
	(0.055)	(0.053)	(0.051)	(0.050)	(0.051)	(0.051)
Distance to Town (log)				0.035	0.123	0.077
				(0.164)	(0.152)	(0.172)
Number of Households (log)				−0.486**	−0.181	−0.240
				(0.229)	(0.202)	(0.208)
Percent Scheduled Caste/Tribe				−0.027***	−0.016**	−0.010
				(0.008)	(0.006)	(0.007)
State FE?	No	Yes	No	No	Yes	No
District FE?	No	No	Yes	No	No	Yes
Observations	592	592	592	592	592	592

Standard errors clustered at district level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esd.2018.02.004.

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