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Influence of improved supply on household electricity consumption - Evidence from rural India

Shalu Agrawal [a, *], S.P. Harish [b], Aseem Mahajan [c], Daniel Thomas [d], Johannes Urpelainen [e]

[a] Council on Energy, Environment and Water, USA
[b] College of William and Mary, USA
[c] Harvard University, USA
[d] Columbia University, USA
[e] Johns Hopkins SAIS, USA

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ABSTRACT

Even as India pursues universal electricity access, household electricity consumption remains poorly understood. Studies have investigated residential electricity consumption, but most focus on urban consumers, even though a majority of the newly electrified households are in rural areas. Using primary data from 10,000 households, we investigate rural electricity consumption in 200 villages in Uttar Pradesh, Bihar, Odisha, and Rajasthan. We rely on energy use surveys that capture appliance use and multiple energy sources. We find that the surveyed households typically consume 39.3 kWh per month during the summer months, which is half of the country's average residential consumption. We also find that hours of grid-electricity supply predicts consumption: every 1% increase in supply hours is associated with a 1.245% increase in consumption. Our findings suggest that improved supply can lead to significant welfare gains for consumers, and allow distribution companies to tap into unmet electricity demand in rural areas.

1. Introduction

Electricity access can significantly improve the quality of life in rural areas. At the household level, access to electricity can have tangible effects on the quality of lighting, the ability of individuals to engage in leisure, and economic productivity, leading to concrete increases in income over the long term [1]. In India, successive governments have undertaken efforts to improve electricity access in the country. Between 2001 and 2016, half a billion people in India gained access to electricity, doubling the share of electrified households to 82% [2]. Household electrification gained further pace with the launch of the Saubhagya scheme in September 2017, under which 26.3 million households have been provided electricity access [3].[1] As of November 2019, almost all willing households have been electrified either through the central grid or decentralised renewable energy systems.

India is closer to the goal of universal electricity access. But, it is still far away from ensuring reliable and high quality power supply [4]. Large swathes of rural areas in the country face prolonged power cuts [5]. Power distribution companies (discoms) have been tasked to provide 24*7 power supply, but a limited understanding of residential electricity use prevents effective demand and supply management. Chunekar, Varshney and Dixit [6] attribute this to the lack of information about consumption patterns in the public domain. A high share of unmetered connections and the phenomenon of load shedding, also make it difficult to capture uncurtailed electricity use by residential consumers. Only a few studies have explored the issue of household electricity consumption and its drivers in India. Those which do, focus mainly on urban consumers, even though the challenge of electricity access and the share of newly electrified households is greater in rural India. The fact that India has both electricity surplus as well as unmet demand due to power curtailments [7], speaks volumes about the intricate nature of this problem.

This paper investigates electricity use in rural households in India and the factors that influence it, with a focus on the effect of improved supply on consumption patterns. We use detailed microdata from a primary survey of more than 10,000 households spread across 200 villages in four Indian states. We use the information

* Corresponding author.
E-mail address: shalu.agrawal@ceew.in (S. Agrawal).

[1] Pradhan Mantri Sahaj Bijli Har Ghar Yojana (Saubhagya).

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about appliance ownership and usage pattern to estimate electricity use from all possible electricity sources. We then employ a Tobit model to investigate the key determinants of consumption; a significant share of households does not use any electricity, i.e. are censored at zero. We also conduct simulations to estimate the effect of improved supply on electricity consumption at the household and village level. This allows us to estimate latent electricity demand in the surveyed households and villages. We then extrapolate the results to assess the effect at the state level to determine the scale of additional demand that discoms may be required to meet in a scenario of uninterrupted power supply.

The rest of this paper is structured as follows. Section 2 discusses the literature on drivers of household electricity consumption. Section 3 covers the data collection and research methodology. We present the results in Section 4 and discuss the policy implications in Section 5.

2. Household electricity consumption and role of supply-side attributes

This paper contributes to growing literature on household electricity use, particularly in the context of rural populations and developing countries. Filippini and Pachauri [8] use consumer-expenditure survey data to estimate the price and income elasticity of electricity demand for urban households in India. Tso and Yau [9] employ different techniques, such as regression, neural networks and decision tree analysis, to investigate determinants of household electricity demand in Hong Kong. Louw et al. [10] analyze electricity use in low-income households in South Africa, with the help of metered consumption data. Zhou and Teng [11] assess the factors influencing the electricity demand of urban households in China with the help of linear regression. Bekele, Negatu and Eshete [12] do a similar analysis for households in Addis Ababa, Ethiopia.

These studies attribute the variation in household electricity use to diverse factors ranging from socio-economic and dwelling characteristics to appliance ownership and geographic factors (see Jones, Fuertes and Lomas [13] for a systematic review). Demographic and social factors include age and education of the household head, religion and social status of the household, and the number of occupants [14]. Similarly, households with higher economic status or incomes are more likely to have electricity connections [15] and thus, consume more electricity [16]. There is also evidence that households'willingness to pay for improved electricity services increases with income [17]. Other factors, such as the number of rooms and appliance inventory, particularly high load appliances, are also important predictors of consumption patterns[18].

Besides the user characteristics, supply-side attributes also influence electricity usage, though only a few studies have explored this relationship. A study focussed on rural households in India found that the quality of electricity supply influences the household's decision to adopt electricity, more than the household's expenditure [19]. However, this study looks at energy access as a binary outcome, when it is in fact multi-dimensional in nature, as factors like supply duration and quality determine the level of access [20]. Using the 2005 India Human Development Survey (IHDS), Khandker, Barnes and Samad [21] found that improved electricity supply at the village level can help reduce energy expense and hence energy poverty in Indian households. However, they use energy expenditure as a proxy for consumption. Though useful in the absence of actual consumption estimates, it is an imperfect proxy due to variations in electricity tariffs as well as metering rates across states. Based on a comprehensive review of literature Riva et al. [22] illustrate how the energy-development nexus is a complex phenomenon, in which power unreliability is a crucial exogenous factor that negatively influences electricity demand.

These studies establish that power supply influences consumer choices regarding electricity adoption and use. However, they do not analyze the effect of improved supply on electricity use. Due to this knowledge gap and lack of adequate data, studies that aim to forecast household electricity consumption using bottom-up modelling, such as Ruijven et al. [23] find it difficult to incorporate reliability of power supply during model construction.

Addressing this knowledge gap can yield crucial insights to achieve the policy objective of reliable electricity services to all Indian households. Statistically speaking, a randomised experiment would be most suitable to study the effect of improved supply on consumption. However, this would require data before and after the intervention, which is challenging due to the timelines involved and socio-political concerns. We, therefore, rely on cross-sectional household surveys to collect information about household electricity use.

Our study differs substantially from the previous works, in terms of methodology and scope of analysis. It offers a nuanced understanding of how the user and supply characteristics influence household electricity use in rural areas. We test for all key factors drawing from past studies with the help of a censored regression model while overcoming the endogeneity concerns associated with certain variables. With the help of simulations, we estimate the effect of improved power supply on consumption in the surveyed villages and demonstrate the utility of conducting such an exercise by extrapolating the results at the state level. The study also demonstrates how energy use surveys can be employed to estimate residential consumption, where actual consumption data is either unavailable or difficult to obtain.

3. Research design

This section presents the analytical framework used to estimate household electricity use, details on the sampling strategy and data collection, followed by a discussion of dependent and independent variables. It also summarises the model specifications used for the analysis and the strategy employed for estimating the average effect of supply hours on electricity consumption.

3.1. Framework to estimate household electricity consumption

In rural India, many electrified households lack metered connections, while bill generation and collection are often irregular, which makes the estimation of household electricity use challenging. Past studies by Tiwari [24] and Filippini and Pachauri [8] relied on national-level consumer expenditure surveys to investigate household electricity use. However, these lack comprehensive data on electricity supply and use, which often raises doubts about data reliability and accuracy. So, we rely on energy use surveys to collect data on appliance ownership, power ratings, and usage patterns. The approach allows estimation of electricity consumption from multiple sources, in cases where households stack grid and non-grid sources.

3.2. Sampling and data collection

We conducted a primary survey of 10,049 households spread across 47 districts and 200 villages in the north Indian states of Bihar, Odisha, Rajasthan, and Uttar Pradesh. These four states accounted for 70% of all un-electrified households in the country when the survey was undertaken (April–June 2018). The data was collected in collaboration with Smart Power India to establish a baseline of rural electricity use and study the customer attitude

Table 1
Four categories of villages considered in this study.

Village Category	Abbreviation	Description
Villages with mini-grids	MG villages	Villages having operational SPRD mini-grids. There are 91 such villages spread across 19 districts in Uttar Pradesh and Bihar.
Villages without mini-grids	Non-MG villages	Villages in the same districts as SPRD mini-grids.These do not have mini-grids at present.
Villages with distribution franchise	DF-villages	Villages in the districts being served by the distribution franchises. These are located in eight districts of Odisha.
Villages with public discoms	Non-DF villages	Villages in select 20 districts from the four states, which could be prospective sites for distribution franchises.

towards electricity services under three delivery models - public distribution companies (discoms), private distribution franchises and solar mini-grids [25].[2]

We sampled 200 villages in a purposive manner from sampling frames of villages having solar mini-grids or distribution franchises, and similar villages served by public discoms. We first created a sampling frame for each of the four village categories, as described in Table 1. From each sampling frame, we randomly selected 50 villages without replacement, in proportion to the number of villages per district, but blocking the sample by the district, in order to ensure at least one village from each district. It was also ensured that the sampled villages were similar to mini-grid (MG) villages along two covariates: the total village population and distance of the village from the nearest town. For this purpose, only villages within one standard deviation of the mean of these covariates for MG villages were included in the sample frame. Within each village, we randomly sampled 50 households. Given the sampling design, the sample is not representative at the state level.

We employed an experienced survey company for data collection. The questionnaire focussed on information about electricity sources, appliance ownership and usage, and socio-economic characteristics of the households. The surveys were conducted in the local languages and administered via hand-held tablets.

3.3. Dependent variable

We use monthly electricity consumption of households in kilowatt hours (kWh) as the dependent variable. This is estimated using the following formula:

$$E_j = \Sigma_i (W_{ij} * H_{ij} * 30)$$

Where E_j is the monthly electricity consumption of j^{th} household, i is the type of electric appliance, W_i is the power rating of i^{th} appliance in Watts, H_i is the total daily hours for which households use the i^{th} appliances.

We have comprehensively checked the survey data related to appliances. We asked the respondents about the power rating of their appliances. In some cases, reported values appeared to be technically incorrect. So, we winsorised the wattage data with the help of reasonable assumptions (see Table 2).[3] These values were identified by triangulating data from multiple sources: surveys

Table 2
Assumptions used to process appliance power rating variables in the survey.

S. No.	Appliance name	Lower bound	Upper bound	Mean values
		(All values are in Watts, unless specified)		
1	Incandescent bulb	3	200	97
2	CFL	2	100	16
3	LED	2	40	8
4	Tube light	5	70	27
5	Mobile charger	5		
6	Ceiling fan	20	120	69
7	Table fan	10	120	61
8	TV	14 inch	55 inch	21 inch
9	Cooler	60	750	224
10	Electric stove	500	3000	1192
11	Laptop	50		
12	Refrigerator	41.32 (equivalent to a 260 L direct cool refrigerator)		
13	Electric iron	450	2500	858
14	Grinder/Mixer	100	1000	376
15	Music system/Radio	15		
16	Air conditioner	1 ton	1.5 ton	1 ton
17	Washing machine	400		
18	Fodder cutting machine	1 HP	5 HP	2 HP
19	Water pump	0.5 HP	10 HP	2 HP

with owners of electrical appliance shops, average values from the survey, and secondary research. Many respondents were unaware of power ratings, particularly for non-lighting appliances. Such missing data points were assigned mean values from the survey data. For appliances such as washing machines, music or radio system, mobile phones, and laptops, we identified power ratings using secondary research. In the absence of actual consumption data, we assume that all appliances consume rated power, although this is not always true.

3.4. Independent variables

In line with the findings of past studies, we include all the relevant household and village level characteristics in our model. These are discussed below.

Social group. The surveyed households belong to four broad categories: scheduled caste (19%), scheduled tribe (4%), other backward castes (53%) and general category (24%). To account for inequities in access to energy services [14], we use *scheduled caste/tribe* as a dummy variable. We capture household religion through a dummy variable, *Muslim*, where 1 represents Muslim households.

Education. We collected information on the highest level of education received by the primary decision-maker of the household. For simplicity, we represent education using three dummy variables: *education - none* (base level), *education - up to class* 9th and *education - class* 10th *and above*. We expect households with more educated decision-makers to have higher electricity consumption, due to a better understanding of the benefits of electricity and procedures to avail it [8].

[2] Under the distribution franchise model, public discoms outsource their electricity distribution activities to private players to reduce losses, improve operational efficiency, and ensure improved customer service.

[3] We estimated TV wattage as *0.18 * screen area*; screen area (in square inches) was calculated using an aspect ratio of 16:9. For refrigerator, we assumed a standard rate of 362 kWh/year (average consumption of a 260-L direct cool refrigerator), which roughly translates into a watt rating of 41.32 W. For air conditioners, we assumed that 1 ton is equivalent to 1000 Watts; 1.5 tons is equivalent to 2000 Watt; compressor activity rate is 75%. For conversion of HP into Watt, we assumed that 1 HP = 746 Watts.

Household size. The number of household members is also expected to positively influence electricity consumption [26]. The average household size in the sample is 6.5, but it varies widely from 1 to 45. Therefore, we use household size as a continuous variable, albeit in a log format.

Building type. We capture the dwelling type, with *pucca house* as a dummy variable, where 1 and 0 represent houses with permanent and temporary structures, respectively. The former is expected to have higher consumption, as the latter is likely to prioritise investment in building a pucca house over electric appliances. We also test for *number of rooms* in the house, which is represented as a continuous variable (log) and is expected to be positively associated with electricity use [13].

Household economic status. While most studies use household income or expenditure to capture economic status, the presence of electricity has been found to improve income levels [27]. This could raise endogeneity concerns, so we capture household's economic status with two durable assets. First, *land ownership*, which is a dummy variable for households owning agricultural land (60%). Second, *motorised vehicles*, which is a dummy variable for ownership of motorised vehicles, such as motorcycle, car or tractor.

Primary source of income. Previous studies have used the occupation status of the household head (Yohanis, 2008). We represent the primary source of household income through three dummy variables: *Income source - Agriculture* (base level), *Income source - Labor*, and *Income source - Salary/business*. When compared to agricultural households, we expect households relying on a salary or business to have higher consumption (due to a relatively steady source of income) and those engaged in labour to have lower consumption (due to uncertain income flows).

Hours of grid electricity supply. We use the variable *village grid hours* to represent the average hours of grid-supply received by electrified households in a village. The average value is assigned to all households in the village, whether electrified or not. Interruptions in electricity supply can put an upper limit on the duration for which households can use appliances, besides influencing the decision to use grid-electricity in the first place [19].

Years since electrification. We use this variable to capture the years for which grid-electricity is available in a village, measured as the average of years for which households in a village have been using grid-electricity. We expect a positive association with electricity consumption, as early electrification can influence electricity adoption, through better quality service [28], and larger appliance stock, as households stock appliances over time [29,30].

Electricity delivery model. Our study covers villages with different electricity delivery models: villages with solar mini-grids (MG villages) and those without it, but similar to MG-villages (Non-MG villages); villages serviced by private distribution franchises (DF villages) and those serviced by public discoms (Non-DF villages). We construct dummy variables for each of these village categories, to assess whether the presence of mini-grids or distribution franchises is associated with higher electricity consumption, as compared to villages without these interventions.

We control for distance from the nearest town, since village location can influence electrification rates [31]. We also include state fixed effects to account for unobserved state-level differences, such as cultural differences as well as variation in governance, government schemes, and the financial health of discoms. We do not include power tariffs, as many households do not face prescribed power tariffs due to gaps in metering and revenue collection. For instance, 50% of grid-users in the Uttar Pradesh sample do not have electricity meters and only 20% get electricity bills regularly.

Table 3 shows the summary statistics of all explanatory variables. We conducted a correlation analysis for any potential multicollinearity between the independent variables and found none. See Fig. 1.

3.5. Model specifications

A key characteristic of our sample data is that nearly 17% of sampled households have zero electricity consumption, which could be due to limited access to electricity sources. Thus, electricity consumption of such households is not observable, due to which our dependent variable, the monthly electricity consumption, is left-censored at zero. Under such conditions, the dependent variable fails to meet the linearity assumption and the use of Ordinary Least Square (OLS) regression would yield biased and inconsistent estimates [32]. We, therefore, specify a Tobit model which is a censored regression model originally proposed by Tobin in 1958. We assume a latent dependent variable (E_j^*), which is equal to the observable dependent variable (E_j) whenever the latent variable is non-negative. We estimate the following equations:

$$ln\left(E_j^*+1\right)=\alpha+\beta H_j+\gamma V_j+\varepsilon_j,$$

$$E_j=\begin{cases} E_j^*, & \text{if } \mathrm{E_j^*}>0 \\ 0, & \text{if } \mathrm{E_j^*}<=0 \end{cases} \tag{1}$$

Where H_j is a vector of socio-economic and dwelling-related characteristics at the household-level, and V_j is a vector of village-level characteristics related to electricity supply, delivery model and geographic distance. ε_j represents the randomly distributed error term, while α, β and γ are the unknown parameters to be estimated.

We assume the dependent variable to be lognormal, and logarithmize it to account for the high skewness in its distribution (see Fig. 2). This approach has been successfully used to represent non-negative skewed variables [32]. All other continuous and discrete variables are also logarithmized, due to the presence of many outliers. We add the independent variables in a step-wise manner, to assess the variation in the parameter estimates; both

Table 3
Summary statistics for key predictor variables for the entire sample. The mean for dummy variables (with asterisk) represents the share of total households with given characteristics.

Statistic	Mean	St. Dev.	Min	Max
Scheduled caste/tribe*	0.24	0.43	0	1
Other backward caste*	0.53	0.50	0	1
Muslim*	0.11	0.32	0	1
Education- None*	0.33	0.47	0	1
Education- Upto class 9*	0.43	0.50	0	1
Education- Class 10 and above*	0.23	0.42	0	1
Household size	6.45	3.37	1	45
Household size (ln)	1.74	0.50	0.00	3.81
Number of rooms	2.68	1.58	1	19
Number of rooms (ln)	0.84	0.54	0.00	2.94
Pucca house*	0.53	0.50	0	1
Income source- Agriculture*	0.28	0.45	0	1
Income source- Labour*	0.47	0.50	0	1
Income source- Salary/business*	0.25	0.43	0	1
Land ownership*	0.58	0.49	0	1
Motorised vehicles*	0.34	0.47	0	1
Village grid hours	14.32	4.47	0.00	22.50
Village grid hours (ln+1)	2.67	0.40	0.00	3.16
Years since electrification	7.33	4.19	0.00	27.45
Years since electrification (ln+1)	1.98	0.56	0.00	3.35
Distance to town (km)	17.79	10.27	0	78
Distance to town (ln+1)	2.78	0.59	0.00	4.37

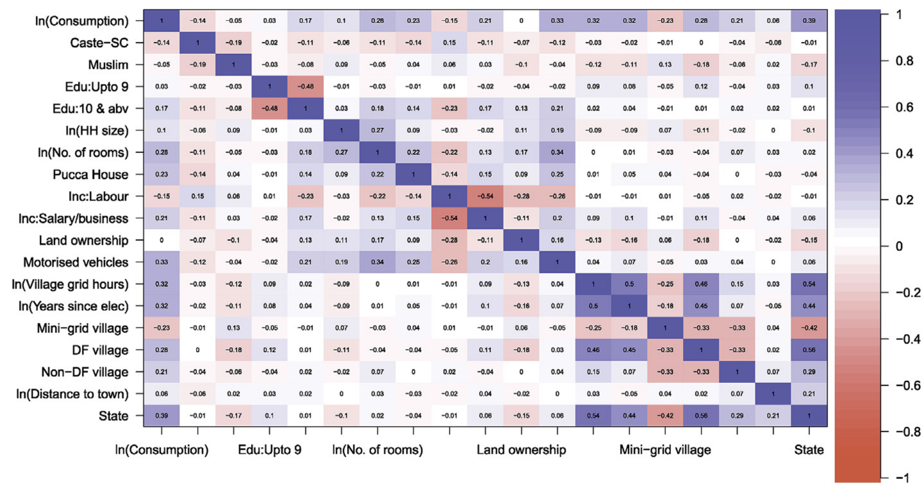
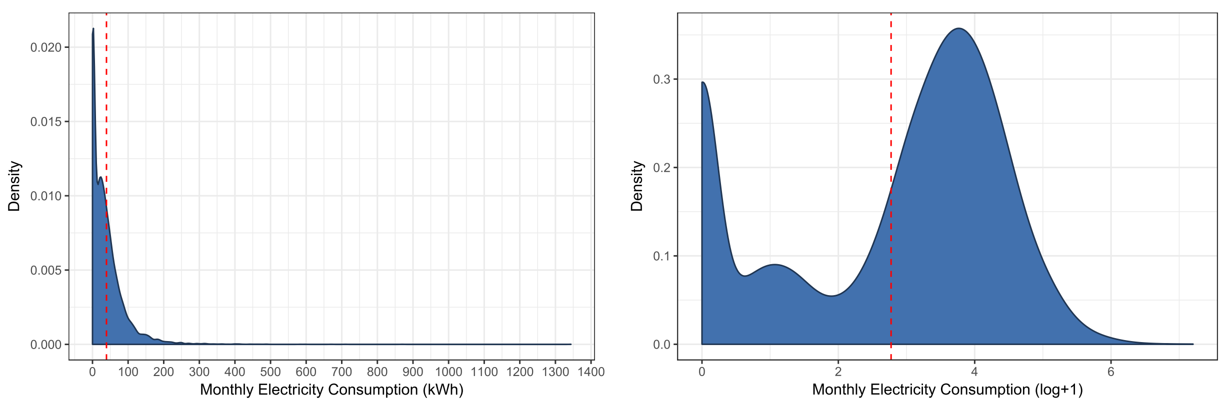


Fig. 1. Correlation plot for the dependent and independent variables. It shows that none of the independent variables are strongly correlated with other independent variables.



(a) Density plot for electricity consumption (b) Density plot for electricity consumption (ln+1)

Fig. 2. Monthly electricity consumption of the sample households. Figure (a) shows the skewed consumption pattren; dashed line represents the sample mean. Figure (b) shows that the logarithmized consumption has near normal distribution, though 17% of the values are censored at zero.

parsimonious and exhaustive models are presented. In all cases standard errors are clustered at the village level, to account for the village clustered sampling strategy. The Tobit model can yield inconsistent estimates if the errors are non-normal or heteroskedastic. So, we conduct robustness checks and find that the residuals are normally distributed (Figure S1 in the Appendix).

3.6. Estimating effect of hours of supply on electricity consumption

With the help of regression results, we also estimate the effect of village grid hours on household electricity use. We employ the algorithm proposed by Ref. [33] to estimate the expected value of a dependent variable while varying the predictor variable. We conduct the effect analysis at both the household and village level.

Case 1. *Effect of electricity supply on the consumption of a representative household.* We construct a representative household using the sample characteristics. All continuous and dummy independent variables are assigned mean and median values, respectively. We vary the value of the predictor between one standard deviation of the sample mean and capture estimation uncertainty by simulating values of the effect coefficients (β).[4] We report the mean, confidence interval and first differences of the expected values of electricity consumption with varied village grid hours, based on 1000 simulations of the effect coefficients. Since our model includes state fixed effects, we report state-wise results.

Case 2. *Effect of electricity supply on village level electricity consumption.* Villages sampled in this study typically have 700 households (median value), with varying socio-economic condition. We construct a representative village for each state by sampling 700 households with replacement from the original sample of each state. We predict the electricity consumption of each

[4] For this purpose, we first estimate the log-log model, which is used to simulate the values of effect coefficients (β). Next, we construct X_c matrix, which contains the values of independent variables. Using the β values and X_c matrix, we estimate the systematic component ($X_c \times \beta$), i.e. the expected value Y_c, which is in log format. We exponentiate Y_c, to obtain expected electricity consumption, after setting the negative fitted values to zero (Tobit model construction).

Table 4
Electricity sources used by sampled rural households. The numbers add up to more than 100, as 9% of households use multiple sources.

#	Statistic	Overall sample	Sample grouped by states			
			Uttar Pradesh	Bihar	Odisha	Rajasthan
1	Sample size	10,049	4788	1403	3108	750
2	Central grid users	75%	58%	91%	90%	92%
3	Solar mini-grid users	2%	4%	1%	0%	0%
4	Solar home system users	9%	16%	10%	0%	0%
5	Rechargeable battery users	5%	8%	5%	1%	1%
6	Diesel generator users	1%	1%	3%	0%	0%
7	Households with no electricity source	17%	26%	7%	10%	8%
8	Average hours of grid supply at village level	14.3	10.8	14.7	19.1	16.6

household while varying the hours of electricity supply; all the negative fitted values are set to zero in view of the Tobit model design. Village level electricity use is estimated by adding the predicted electricity use of all households. This process is repeated 1000 times for each state by re-sampling 700 households with replacement from the state sub-sample. We report the mean and 95% confidence interval for the village-level estimates.

4. Results

4.1. Characterising electricity consumption of rural households

As per the survey findings, around 75% of the rural households in the study area use central grid electricity. The share of grid-users is above 90% in the villages surveyed in Bihar, Odisha and Rajasthan, but less than 60% in the villages surveyed in Uttar Pradesh. We also find that 16% of sampled households use non-grid electricity sources, half of which also use grid-electricity. This suggests that even grid-connected households stack non-grid sources for back-up during power outages.

The share of non-grid users is highest in villages from Uttar Pradesh, which get fewer hours of grid-electricity supply and have the lowest share of grid-users (see Table 4). In these villages, non-grid sources play an important role in facilitating electricity access. Here, solar home systems followed by rechargeable batteries are the most popular grid-alternatives. The use of diesel generators (personal or operator-run) is marginal, mainly due to the high per-unit cost.

We estimate household electricity consumption using the information on appliance ownership, power rating and daily use patterns. We find that the surveyed households consume 39.3 kWh (units) per month on average. This is equivalent to a per capita annual consumption of 87 kWh, which is almost half of the country's average residential consumption (152 KWh) [6].

We also find that household electricity use varies with the type of electricity source. Grid-electricity users in the survey consume 50.6 units per month on average.[5] This is six times the consumption of households using only solar home systems and 15 times that of households using only mini-grid electricity. This is mainly due to limited electricity services derived by non-grid users, as shown in Table 5.[6]

The electricity consumption also varies widely across households. While 17% of households do not use any electricity at all, 37% use up to 30 units/month and another 38% use up to 100 units/month. Only 8% of households consume more than 100 units/month. Overall, most of the surveyed households have low electricity consumption, mainly limited to lighting, cooling and entertainment purposes. The reliability of these estimates rests on the ability of the respondents to recollect information about appliance ownership and use. This may raise concerns about the accuracy of our estimates. But such an approach was a necessary evil, due to the lack of relevant micro-level consumption data.

4.2. Factors influencing electricity consumption

We conducted Tobit regression analysis with household monthly electricity consumption as the dependent variable, in natural log format. Table 6 presents the estimates for three different models. Model (1) contains the socio-economic and dwelling related variables, model (2) includes supply-related variables and Model (3) contains dummy variables for villages with different electricity delivery models and a variable to control for the distance of the village from the nearest town.

Our results suggest that almost all the socio-economic variables are highly significant. Households belonging to scheduled caste/tribe have lower electricity consumption than others, despite controlling for economic factors. This is consistent with past findings that lower social status in Indian society can limit access to basic necessities, such as electricity [14]. In contrast, electricity use is positively associated with the highest education level of the primary decision-maker and the effect coefficient increases with the level of education. Households with heads educated up to class 10^{th} or more consume roughly 30% more electricity on average than those with illiterate heads, even after controlling for their assets. This potentially reflects the difficulty faced by the latter in getting access to electricity. In our sample, two-thirds of the households without grid-connection have illiterate household heads. The association between consumption and religion is, however, inconclusive, as the variable *Muslim* assumes significance in only one of the three models.

There appears to be a strong association between household economic status and electricity consumption. The ownership of motorised vehicles, pucca house and the number of rooms in the house, all of which are associated with higher economic status, have strong positive coefficients, across all models. We also find that the variable *Income source: labour* has a small coefficient with low significance. This suggests that electricity consumption of households relying on labour work is similar to that of agricultural households, potentially due to uncertain income flows in both cases. In contrast, households deriving income from salaried jobs or businesses consume 40% more electricity on average than agricultural households. This underscores the importance of a stable source of income in determining household electricity use. The variable land ownership has a positive but rather small coefficient, potentially because other economic variables better reflect household economic status.

[5] As per the National Sample Survey data (2011–12), the national average of electricity consumption of grid-connected rural households is 68 kWh/month (Saxena and Bhattacharya, 2018).

[6] To avoid the problem of attribution, only exclusive users of each electricity source are considered here.

Table 5
Electricity services derived by rural households using different electricity sources. Space cooling includes the use of fans, coolers or air conditioners; entertainment includes televisions, laptops or music systems; kitchen appliances include refrigerators or food processors; housekeeping includes washing machines, electric irons or water pumps.

#	Electricity services	Electricity source used by rural households				
		Grid electricity	Solar mini-grid	Solar home system	Battery	Diesel mini-grid
1	Lighting	100%	100%	73%	76%	89%
2	Mobile charging	83%	77%	64%	47%	83%
3	Space cooling	86%	7%	23%	2%	6%
4	Entertainment	46%	1%	3%	1%	0%
5	Kitchen appliances	14%	0%	0%	0%	0%
6	Housekeeping	10%	0%	1%	0%	0%
7	Average electricityconsumption (kWh/month)	50.6	3.4	8.5	1.9	4

A key finding of this study is that households in villages getting longer hours of electricity supply, on average, have higher consumption, even after controlling for other factors. Results from Model (2) suggest that every 1% change in grid supply hours is linked with a 1.245% change in household consumption. Previous studies have discussed the role of electricity supply in influencing electricity adoption [19] and use (proxied by energy expenses) [34] but felt short of exploring the influence on actual consumption.

Table 6
Tobit model estimates of household electricity consumption, for the entire sample. Models (1) to (3) represent the results with the inclusion of different variables in a step-wise manner.

	*Dependent variable:*Electricity Consumption		
	(1)	(2)	(3)
Scheduled caste/tribe?	− 0.252***	− 0.207***	− 0.166***
	(0.071)	(0.066)	(0.061)
Muslim?	0.125	0.109	0.205***
	(0.095)	(0.080)	(0.078)
Education: Upto class 9?	0.156***	0.133***	0.151***
	(0.049)	(0.045)	(0.043)
Education: Class 10 n abv?	0.328***	0.284***	0.288***
	(0.059)	(0.049)	(0.047)
ln(Household size)	0.189***	0.216***	0.205***
	(0.041)	(0.039)	(0.037)
ln(Number of rooms)	0.573***	0.539***	0.519***
	(0.049)	(0.046)	(0.042)
Pucca House?	0.495***	0.412***	0.416***
	(0.051)	(0.045)	(0.043)
Income source: Labour?	0.093	0.008	0.028
	(0.068)	(0.057)	(0.052)
Income source: Salary/business?	0.415***	0.335***	0.335***
	(0.067)	(0.058)	(0.052)
Land ownership?	0.006	0.057	0.105**
	(0.052)	(0.048)	(0.043)
Motorised vehicles?	0.651***	0.606***	0.585***
	(0.044)	(0.042)	(0.042)
ln(Village grid hours)		1.245***	0.924***
		(0.280)	(0.209)
ln(Years since electrification)		0.406***	0.397***
		(0.102)	(0.088)
Mini-grid village?			0.054
			(0.117)
DF village?			1.390***
			(0.218)
Non-DF village?			0.963***
			(0.132)
ln(Distance to town)			0.003
			(0.072)
Observations	10,049	10,049	10,049
Log Likelihood	− 17,603.180	− 17,236.030	− 17,058.770
Wald Test	4373.926*** (df = 14)	5242.002*** (df = 16)	5840.405*** (df = 20)
Note:	*p < 0.1; **p < 0.05; ***p < 0.01 State fixed effects included.		

We also find that households in villages electrified earlier have relatively higher consumption. Early electrification of the village implies that over time more households take electricity connection (due to neighbourhood effects) and stock appliances. We observe a moderate correlation (0.5) between early electrification and hours of grid supply, suggesting improvement in power supply over time, which is also linked to higher consumption.[7] The survey data suggests that early electrification and hours of supply influence electricity use through two endogenous variables: adoption of grid-electricity and appliance stock. However, the inclusion of these endogenous variables can compromise the model's robustness; these are also moderately correlated with other independent variables (grid supply hours and years since electrification).

Another interesting finding pertains to the village level dummies for the type of delivery model. Model (3) results show that the presence of a solar mini-grid in a village does not have any significant influence on the average household electricity consumption as compared to a similar village without a mini-grid (base level). This is because i) both categories of villages are grid-connected, ii) only a few households (7.5% on average) use mini-grid electricity in the MG villages, and iii) mini-grid connections are mainly used for basic lighting and mobile charging purposes. In contrast, the coefficients of DF village (representing villages with distribution franchise) and non-DF village are positive and significant, implying higher consumption on average as compared to villages without mini-grids. This may be partly due to the fact that these villages have a higher penetration of grid-electricity and receive longer hours of electricity supply. We also observe that the coefficient of the DF village variable is higher than that of the non-DF village, suggesting that villages being serviced by private distribution franchises have higher consumption, as compared to those serviced by public discoms. However, this may also be due to a systematic difference in the areas serviced by distribution franchises and public discoms (selection bias). Future studies could investigate whether private distribution franchises are able to cater to rural electricity demand better than public discoms.

We also conduct a linear regression analysis, for robustness check, and Appendix S2 compares the Tobit estimates with OLS estimates. It can be seen that OLS estimates are generally lower (biased), as this approach does not consider the fact that some households do not use electricity when the supply is bad or simply not available. When asked to state the reasons for not using grid-electricity, 20% of the un-electrified households in our sample cited the inability to get connections and 7% cited a lack of reliable and quality supply. The use of OLS model would have implied an underestimation of the association between electricity supply and consumption. Tobit model helps overcome this bias.

4.3. Effect of hours of supply on electricity consumption

In this section, we estimate the effect of varying hours of grid-electricity supply on electricity consumption of a representative household and at village-level.

1. Electricity consumption of a representative household.[8] Using the procedure described in section 3.6 and the results of the model (2) as shown in Table 6, we estimate the expected electricity consumption of a representative household for each state. We find that for all values of hours of supply, the expected electricity consumption is highest among households sampled from Rajasthan, followed by Odisha, Bihar and Uttar Pradesh, in that order (Fig. 3 (a)). Upon increasing the supply from the average value (14.32 h) by one standard deviation (4.47 h), household use increases by 40%, which is quite significant. This first difference is 10.9 (8.2–13.6) units per month in Rajasthan, 7.56 (7.24–7.56) units in Odisha, 7.5 (5.1–10.3) units in Bihar and 3.62 (1.8–6.5) units in Uttar Pradesh.[9] To put these numbers in perspective, a 50 W fan running for 5 h a day consumes 7.5 units of electricity in a month.

We also estimate the average effect of 1 h increase in grid supply on electricity use.[10] Fig. 3 (b) shows that the average effect of grid supply hours varies from 0.77 units per month in Uttar Pradesh to 2.34 units per month in Rajasthan. The results suggest that the effect of supply hours is higher on households with higher consumption, implying that improved supply could help discoms generate more revenue from high paying consumers.

Household electrification rates have risen ever since the survey was conducted in early 2018. With the higher share of households electrified, the average effect of hours of supply on household electricity consumption is likely to be even higher (Fig. 4). However, these results cannot be generalised to un-electrified households, which are systematically different from electrified households.[11]

2. Household electricity consumption at the village level. Fig. 5 displays the predicted household electricity consumption of a typical village covered in this study.[12] We find that the average electricity consumption of a village with 700 households, receiving average hours (14.32) of grid supply varies from 9000 units per month in Uttar Pradesh to more than 28,000 units per month in Rajasthan. Increasing the supply hours from the average value by one standard deviation (4.47 h) increases the monthly electricity consumption of a typical sample village by 3350–10,750 units per month or an increase of 37%. This is equivalent to an additional consumption of 1.04–3.31 units per month per household, for every 1 h increase in grid supply. Thus, the cumulative effect of improved power supply on village level electricity consumption is non-trivial, even though the effect at the household level appears small in absolute terms.[13]

It must be noted that the village population varies vastly within and across states.[14] Further, this study does not cover small villages (populations smaller than 2000), due to which these results cannot be generalised for all villages in the concerned states.

Even though our sample is not representative of all villages in the states, we extrapolate these results to all rural households within each state. Table 7 shows that an hourly increase in grid supply would imply an additional consumption of 20–40 million units from all rural households in the focus states. As a share of state-wide electricity consumption from all sectors, this amounts to a 0.26–1.83% increase, highest in Bihar and lowest in Uttar Pradesh.[15] In fact, a transition to uninterrupted supply from current levels of supply would imply an additional consumption of around

[7] The variance inflation factors for these two variables is less than 2.5, which confirms the absence of any multicollinearity concerns.

[8] Characteristics of a representative household: Hindu household; 6 members; not belonging scheduled caste; household head educated up to class 9th; pucca house; 2.7 rooms; owns agricultural land; labour as the primary source of income; village got electrified more than 7 years ago and is 18 km away from nearest town.

[9] Values in brackets indicate the 95% confidence interval for these estimates.

[10] Ratio of net increase in electricity consumption with two standard deviation increase in supply to two times the standard deviation of village grid hours.

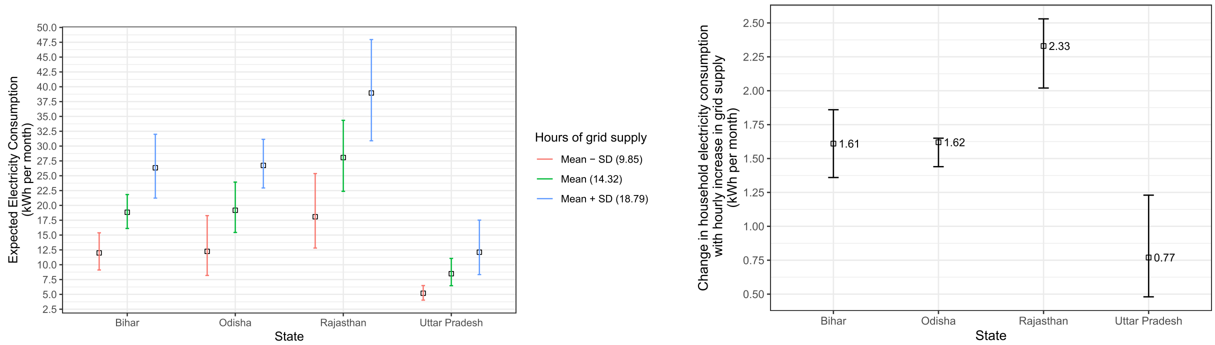
[11] Un-electrified households in the sample have lower education levels, smaller houses and lower expenditures as compared to electrified households.

[12] Unlike expected values, which capture only estimation uncertainty, predicted values also capture fundamental uncertainty. As households within a village are heterogeneous, we simulate predicted values for village level electricity use.

[13] To put these numbers into perspective, a 25 kW solar micro-grid typically generates 3240 units of electricity per month, at a capacity utilisation factor of 0.18.

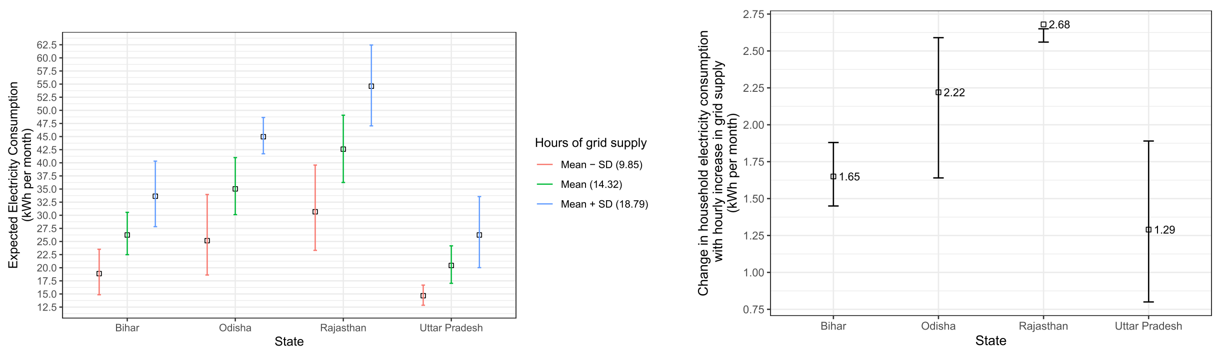
[14] On average, villages in Bihar, Odisha, Rajasthan and Uttar Pradesh have 433, 159, 212 and 260 households, respectively.

[15] As per state-level energy requirements for the year 2017–18 [37].



(a) Variation in expected electricity consumption (b) Average effect of hourly increase in supply

Fig. 3. Influence of hours of grid supply on household electricity consumption for each state sample. The squares represent average values at different supply hours, while error bars represent 95% confidence interval corresponding to estimation uncertainty.



(a) Variation in expected electricity consumption (b) Average effect of hourly increase in supply

Fig. 4. Influence of hours of grid supply on household electricity consumption, when considering only electrified households.

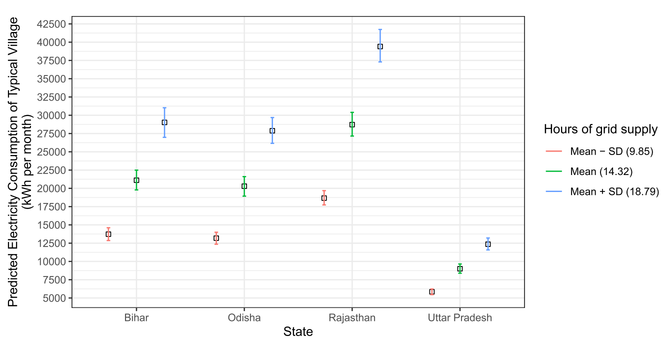


Fig. 5. Variation in village-level household electricity consumption with hours of grid supply.

15% in Bihar, and 3.5–4% in other states. These numbers reflect the extent of unmet electricity demand in rural areas due to power curtailments in the focus states.

4.4. Study limitations

A key limitation of this study is that the results are based on cross-sectional data and are not amenable to causal interpretation. This is mainly a concern because the energy-development nexus is complex and consumption is often correlated with development-based indicators [22]. For instance, household incomes, education levels and local economic activity may improve with electricity access; however, in order to realise these gains electrification needs to be supported by complementary actions and investments in rural infrastructure [27]. We have tried to overcome some of these concerns, by excluding potential endogenous variables, such as grid-connection, household expenditure, and appliances, and by clustering the standard errors at the village level.

For village grid hours, our explanatory variable, it is unlikely that the availability of electricity supply would change because of individual consumption. However, it is possible that the supply hours are correlated with household willingness to pay (a latent variable)

Table 7
Effect of improved power supply on electricity consumption of rural households at the state level.

Statistic	Bihar	Odisha	Rajasthan	Uttar Pradesh
Change in average consumption of a typical village with one standard deviation increase (4.7 h) in grid supply (units per month)	7895	7599	10,742	3349
Average effect of hourly increase in supply (units per month per household)	2.44	2.35	3.32	1.04
Number of rural households in the state as per Census 2011 (million)	16.93	8.14	9.49	25.48
Average effect of hourly increase in supply on electricity consumption of rural householdsin the state (million units per month)	41.27	19.12	31.47	26.48
State electricity demand in the year 2017–18 (million units per month)	2252	2400	5933	10,004
Change in rural household electricity consumption with an hourly increase in supply as a share of state electricity demand (%)	1.83%	0.80%	0.53%	0.26%

and power cuts may be higher in areas with higher losses due to theft or non-payments of electricity bills. However, this relationship is difficult to capture due to inadequate information. Another limitation of the study is that the findings are not representative at either the state or national level, due to the sampling design.

5. Discussion and conclusions

With near-universal household electrification, provision of an uninterrupted power supply is the next major policy goal in India. A better understanding of household electricity use and its drivers, particularly the influence of improved supply on consumption can help the power suppliers undertake robust planning and provide reliable services. However, this is limited by the lack of adequate micro-level data on household consumption patterns.

In this paper, we share insights based on a primary survey of more than 10,000 households from 200 villages in four Indian states. We estimate household electricity consumption with the help of appliance ownership and usage pattern. We find that households in the focus villages consume 39.3 units (kWh) per month on average, which is just half of the country's average residential consumption. The low consumption levels are mainly due to limited appliance stock, as most households use electricity only for basic lighting, cooling, and entertainment purposes.

With the help of a Tobit model, we find that household's socio-economic and building characteristics are significant predictors of the electricity use. The current consumption levels are linked to housing conditions, education and income levels. But more importantly, we find that hours of grid supply predict consumption: 1% increase in supply hours is associated with a 1.245% increase in household electricity use. While past studies have highlighted this association with the help of proxies, ours is the first study to simulate the effect of grid-supply hours on household electricity consumption.

Our findings have multiple policy implications. From a consumer perspective, improved supply can lead to significant welfare gains by allowing households to use electricity for longer hours, incentivising purchase of new appliances over time, and by attracting new customers. With one standard deviation increase in supply (4.5 h), the consumption of a representative household increases by 40%, which is quite significant.

The findings also point toward a significant amount of unmet electricity demand in rural areas, which the discoms can tap into. With an hourly increase in supply, the electricity use in rural households could increase by 26–41 million units per month, equivalent to 0.26%–1.83% of total consumption at the state level (lowest in Uttar Pradesh and highest in Bihar). In Bihar, a transition from the current levels of supply to 24*7 supply could lead to more than 15% increment in load. This reflects both a vast opportunity as well as the need for adequate planning to meet the additional consumption.

As discussed earlier, the availability of electricity at the national level is not a constraint, yet consumers face supply issues. This is due to factors such as gaps in billing and revenue collection, and the inability of discoms to pass the full cost of supply to consumers [35]. Provision of improved supply along with measures to improve billing and collection efficiency can help discoms reinforce a virtuous feedback loop. This is because the willingness of consumers to pay for electricity increases with improvement in supply services [36]. However, improved supply would likely influence electricity use in an incremental manner over time. As Khandker, Barnes and Samad [27] note, electricity access can reinforce the virtuous cycle of development when complemented by investments in rural infrastructure and enabling services.

The findings of this study are based on energy use surveys, which are important tools of research in the absence of actual consumption data but are vulnerable to errors associated with stated responses. Availability of real-time consumption data in future would facilitate more rigorous research on changing consumption patterns.

Credit author statement

Shalu Agrawal: Conceptualisation, Data curation, Formal analysis, Writing - original draft, S P Harish: Conceptualisation, Writing - reviewing and editing, Aseem Mahajan: Methodology, Writing - reviewing and editing, Daniel Thomas: Writing - reviewing and editing; Johannes Urpelainen: Conceptualisation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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