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Quality of service predicts willingness to pay for household electricity connections in rural India[☆]

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ABSTRACT

While rural electrification has been a high priority for many governments in the developing world, the factors that make individual households more likely to pay for a connection have received insufficient attention. In particular, many studies have dealt with the role of affordability of grid connections, but they have generally avoided studying the effects of service quality. Estimating the effect of quality on willingness of potential customers to pay is a difficult task because of self-selection – if quality is important, those in higher quality service areas are more likely to have a connection. Using household data from rural India, we estimate a Heckman selection model to deal with this issue and find a substantial impact of quality on willingness to pay for a connection in India. The results suggest that improving the quality of connections is critical to improving access.

1. Introduction

Rural electrification is both a fundamental prerequisite for economic modernization and a political priority for governments. At the household level, however, decisions to obtain electricity connections – when available – boil down to comparing the costs and benefits. Electricity connections are typically not free, and households must pay for using power. While many studies have rightly identified affordability as an important issue (Winkler et al., 2011; Rahman et al., 2013; Riley, 2014; Alkon et al., 2016), these studies typically do not disentangle whether it is the high cost of service or the low quality of available service that deters consumers. On the one hand, households might consider their local electricity service adequate but too expensive. On the other hand, households might be willing and able to pay but choose not to do so because the quality of the service does not meet their needs.

Answering these questions is of direct policy relevance. If people are unable to pay, even for high-quality service, then the government's focus should be on poverty alleviation and/or reducing the cost of the electricity service. But if the problem is the low quality of service, then improving it is key to increasing household electrification rates. In India, for example, Prime Minister Modi announced in September 2017 a new *Saubhagya* scheme that offers free or heavily subsidized electricity connections to rural households. This scheme reduces the cost of electricity connections, but it does not offer solutions to the problem of low-quality electricity service. Understanding the importance of service quality is thus important to evaluating the prospects of subsidized household connectivity as a strategy.[1]

To understand the relationship between the quality of electricity service and willingness to pay, we use the 2014–2015 ACCESS survey with data from 714 villages on over 8500 rural households from six states of India. The survey data allows us to estimate the quality of electricity service at the village level and also gives us the stated willingness to pay among households that are not currently connected to the grid. Thus, we can explore the role of service quality in explaining willingness to pay for electric grid connections among households. The results can, in turn, contribute to rural electrification planning by measuring the value of connecting households to the electric grid.

Our key methodological innovation is to apply selection models (Heckman, 1979) to understand the relationship between the quality of service and willingness to pay (WTP). In theory, households that are already electrified also have a willingness to pay, but unfortunately collecting such data with surveys is virtually impossible. Households that are currently electrified cannot answer the same question that non-

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[1] See http://pib.nic.in/newsite/PrintRelease.aspx?relid=171148 (accessed December 5, 2017).

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electrified households answer – how much would you be willing to pay for a household electricity connection. They would, instead, answer a different survey question: how much would you be willing to pay if you did *not* already have a connection? It is true that these households' decisions to purchase electricity provide some information about their willingness to pay for it, but such measurements are imprecise. Because subsidized electricity can be purchased at below-market prices, their willingness to pay for it only provides a lower bound estimate of their true willingness to pay. Moreover, the costs of household electricity connections vary across geography and over time, meaning that already connected households made their decisions facing different costs. We overcome the problem of ascertaining individuals' true willingness to pay by applying selection models to ensure that the non-random selection of households into the non-electrified group does not bias our results.

Our results confirm the importance of high-quality service for willingness to pay for household electrification. We use three different measures of the quality of electricity service (daily total hours available, hours available at night, and a quality index that also considers outages and voltage fluctuation). We uncover evidence for a large and statistically significant association between quality and willingness to pay. Substantively, a 1 h increase in total hours available would increase WTP by about 56 rupees (USD 0.87), a 1/10 point increase in the quality scale would increase this by about 251 rupees (USD 3.89), and a 1 h increase in nighttime hours would increase WTP by about 160 rupees (USD 2.48). To put this into context, the average non-electrified household in the survey reported being willing to pay 399 rupees (USD 6.18) for an electricity connection.

To our understanding, this is the first study to estimate the relationship between quality of electricity service and WTP. Existing studies have shown that the quality of service is a key predictor of subjective satisfaction (Aklin et al., 2016) and productive uses (Chakravorty et al., 2014). They have also identified the effect of outages on household connectivity (Millien, 2017), but we are not aware of any studies that model the role of the quality of service in non-electrified households' WTP. Our results confirm the importance of high-quality electricity service and thus make a strong case for power sector reforms that contribute to the improvement of service quality in rural areas.

2. Willingess to pay for household electrification

The electrification of villages and households carries costs, and studies of rural electrification identify the fixed and variable costs of electricity as important barriers to universal electrification (Foley, 1992; Barnes, 2014; Alkon et al., 2016). Although many governments offer generous subsidies for household connections (Barnes, 2007), empirical studies identify the *affordability* of power as a key reason why many households in poorer countries remain without electricity (Haanyika, 2006; Mainali and Silveira, 2011). According to this line of argumentation, economic poverty is a key explanation for energy poverty. The policy recommendations around these concerns deal primarily with government subsidies or methods to change the payment structure for electricity.

While affordability is important, it cannot be considered in isolation from *willingness to pay* for power. Although some households might be so poor that they could not afford household electrification even if they spent all their money on electricity, a more realistic case is that of a household unwilling to spend substantial sums of money on household electrification. Such a household must choose among a number of expenses, ranging from healthcare to education and expenditures for basic items such as housing and food. In deciding whether to pay for a household connection, households compare the value of electricity access against other needs. Indeed, Khandker et al. (2012) note in India that energy poverty and income poverty, while related, do not fully overlap, especially in rural communities. Research examining the relationship between fuel and income poverty has, to date, focused primarily on developed countries (Hills, 2012; Brunner et al., 2012; Howden-Chapman et al., 2012; Thomson and Snell, 2013). Even there, many households in the US, Western Europe, and Australasia face the "heat or eat" tradeoff (Bhattacharya et al., 2003), reducing food consumption in response to higher heating prices in winter (Brunner et al., 2012; Howden-Chapman et al., 2012; Beatty et al., 2014).

Aside from its cost, households consider the benefits derived from consuming electricity. Demand for electricity in poor rural households is generally low and concentrated at evening peak hours (Barnes, 2007). The benefits a household can get from electrification during these times will differ dramatically based on the amount of electricity available. Randomized controlled trials on small solar power systems, for example, have found mixed evidence for health and education benefits, and only weak evidence for economic benefits (Aklin et al., 2017; Grimm et al., 2016). Studies that use various econometric tools to identify the causal impact of strengthening grid electricity connections have generally identified much larger effects on economic well-being (Khandker et al., 2013; Dinkelman, 2011). It is important to note, however, that such benefits are distributed unevenly across households (Khandker et al., 2013) and, when deciding how much a household is willing to pay for electricity, there are definite tradeoffs in terms of alternative usage for household income.

The value of these benefits depends on, among other factors, the quality of electricity service. For economic purposes, a reliable and stable supply of power is more valuable than intermittent access. Chakravorty et al. (2014), for example, find that the non-agricultural income gains from electrification are more than three times higher for those who have high quality connections (defined by hours of electricity per day). Household businesses are difficult to maintain if the energy needed for their functioning is intermittent, especially during peak demand. Evidence from several countries in Africa demonstrates that businesses facing poor electricity infrastructures must self-generate electricity at higher costs (Steinbuks and Foster, 2010; Foster and Briceño-Garmendia, 2010; Alby et al., 2011) and, in China, Fisher-Vanden et al. (2012) find that unreliable electricity decreases productivity in industrial firms. Similar losses are found in India, with the highest costs borne by small businesses that lack generators (Allcott et al., 2014). The productivity losses from poor electricity quality disincentivize firms' investment in productive capacity (Reinikka and Svensson, 1999; Ryan, 2017), leading to further welfare losses for their employees and local small businessowners. Similarly, Aklin et al. (2016) find robust evidence for the importance of the quality of electricity access for subjective well-being in rural India.

3. Research design

To explore the association between the quality of electricity service and WTP, we use the ACCESS survey from six states in rural India (Section A1 contains detailed information). The fundamental problem with evaluating the link between quality and WTP is selection bias: where quality is high, people pay for electric connections and it is no longer possible to observe their stated WTP. Only among non-electrified households can we collect meaningful data on WTP, and due to the necessity of conditioning on this common characteristic, this analysis is greatly complicated by selection bias. To correct for this bias we rely on a two-step Heckman (1979) selection model.[2] Doing so allows us to use the entire sample of households — located in villages that have at least one electrified household — to estimate a model predicting households' probability of non-electrification on the basis of habitation sizes, which

[2] Chambwera and Folmer (2007, p. 2543) use a similar approach when evaluating households' energy choices. The model has also been used for measuring individuals' WTP for healthcare and education (Van de Ven and Van Praag, 1981; Khwaja, 2010; Gertler and Glewwe, 1990).

are conditionally independent of households' WTP.

We estimate the following system of equations:

$$P(\text{ non} - \text{electrified } |Z) = \Phi(Z\gamma) \quad (1)$$

$$E[\ WTP \mid X, \text{non} - \text{electrified}\ ] = X\beta + \rho\sigma_u\lambda(Z\gamma) \quad (2)$$

In the first stage, we estimate the standard probit model (1) to determine the probability of a household *not* being electrified, coded 1 if the household does not have electricity and 0 if they do have electricity. Within the equation, Z is the vector of explanatory variables, including an additional variable that is unique to non-electrification, γ represents the parameter estimates and Φ is the cumulative distribution function of the standard normal distribution. In the second stage, we estimate the WTP using (2), where ρ is the correlation between determinants of propensity to be electrified and the error term of the electrification regression, σ_u is the standard deviation of the error term, and λ is the inverse Mills ratio of at $Z\gamma$.[3] Standard errors are clustered by village because we construct our measure of quality of electricity service at that level.

3.1. Dependent variable

The primary dependent variable is the household head's stated WTP for an electricity connection, in Indian rupees. Heads of households without grid electricity were first asked whether they were interested in having it.[4] Households without grid electricity can be without for a variety of reasons, from lack of access to a grid connection (or living too far away from a power pole) to concerns about the costs or not knowing who to contact (see Section A2.4). Those who did not express interest were coded to have WTP of zero, while those who responded affirmatively were asked how many rupees they would be willing to pay for it.[5] We then used the log transformation of their responses to the WTP variable to reduce skew from outliers. The distributions of the transformed and untransformed dependent variable are provided in Section A2.1.

While stated preferences may deviate from revealed WTP, for our purposes it is sufficient that the stated WTP responds to factors such as the quality of electricity supply. Moreover, the average WTP in our sample is 380 Indian rupees, a plausible value given that the typical connection cost remained above one thousand rupees at the time of the survey.[6]

3.2. Explanatory variables

Measuring the quality of electricity service presents a challenge, as non-electrified households do not have power at home by definition. Therefore, we must find a way to estimate the quality of electricity service using data from outside the household. We achieve this goal by focusing on non-electrified households in villages that have at least one electrified household. We then use the *average* self-reported quality among electrified households to estimate the quality of electricity service at the village level. Overall, we have 547 suitable villages in the dataset.

We operationalize the quality of electricity service in two different ways. First, following Aklin et al. (2016), we use the hours of supply $(0-24)$ on a typical day (available hours).[7] As a robustness check, we use the availability of electricity at night (nighttime hours).[8] Finally, as an alternative, we also construct a quality index from three fundamental components of the quality of electricity supply: (i) total hours $(0-24)$ of electricity available on a typical day[9]; (ii) the frequency of electricity outages[10]; and (iii) the frequency with which electrical equipment suffers due to voltage fluctuations.[11] To construct the quality index, observations were first normalized and then the sum of the rescaled frequencies of voltage fluctuations and outages were subtracted from the rescaled measurements of supply. The transformed statistic was then rescaled to range from 0 to 1. Distributions of the independent variables, provided in Section A2.2, exhibit variation without substantial skew.

A bivariate correlation plot illustrating the relationship between the independent and dependent variables is shown in Fig. 1. There appears to be a weak relationship between WTP and the explanatory variables, though unsurprisingly, the explanatory variables — particularly the supply of available hours and nighttime hours — appear to be correlated. Scatter plots describing the relationship between the independent and dependent variables before implementing the Heckman (1979) correction for selection bias, provided in Section A2.2, offer further details about the relationships summarized in Fig. 1.

3.3. Sample self-selection and instrumental variable

As we noted above, households that are currently electrified cannot answer the same question that non-electrified households answer. The price they are currently paying is also likely to have an anchoring effect on any hypothetical scenario questions. This makes it difficult to directly collect information on the counter-factual – how much they would be willing to pay if they did *not* already have a connection – through direct survey mechanisms. Moreover, the result of this self-selection is likely to be biased against finding a relationship between quality and WTP, since those living in areas with higher quality, and hence greater WTP, are more likely to also have a connection.

To implement the Heckman (1979) model, we must select an instrumental variable that has an effect on selection (receiving an electricity connection), but not on the outcome (WTP). We argue that the total number of households in the household's *habitation* is such an instrument. A habitation, sometimes called a ‘natural village’ or a ‘hamlet,’ is a cluster of households within the administrative unit of a census village. Habitations can be thought of as small and distinct neighborhoods within a census village. The number of habitations within a village can range from one to dozens, depending on village size.

While policy-makers have a clear incentive to focus on electrifying habitations with more households, given that they can electrify more households with lower overall investment, there is no clear expectation of how the number of households would affect WTP. Regardless of the number of households in the habitation, a household's decision to obtain a connection depends ultimately on the perceived costs and benefits. Controlling for a household's characteristics such as wealth and education, habitation size should be irrelevant for WTP. We also demonstrate that this intuition is correct below.[12]

[3] We estimate using both the two-step estimator and the full MLE estimator. Both produce substantively identical results.

[4] “Are you interested in having grid electricity?”

[5] “What amount are you willing to pay to get electricity connection?”

[6] At the time of the survey, households living below the poverty line had access to free electricity connections, but all other households had to pay for their connection.

[7] “How many hours a day is electricity usually available?”.

[8] “For how many hours is electricity usually available between sunset and midnight (till 12 o' clock)?”.

[9] As a robustness check, we also operationalized quality using nighttime availability.

[10] “How many days in the last month has there been no power throughout the day?”.

[11] “How many days in a month have you experienced that electric equipment suffered because of voltage fluctuation?”.

[12] As discussed in Section A2.5, it might be possible for habitation size to be related to WTP indirectly if habitation size is related to the proportion of households with businesses. We find no clear correlation between habitation size and household businesses, nor does it affect our main models when it is included as a control variable.

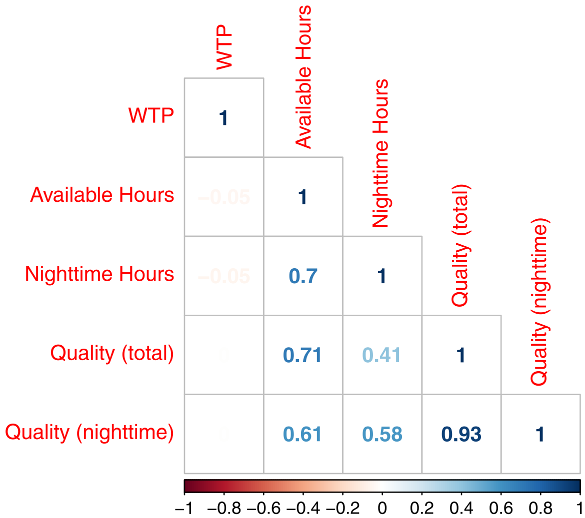

Fig. 1. Correlation plot of non-electrified household characteristics. Aside from non-electrified households' willingness to pay (*WTP*), grid electricity statistics concerning supply and quality are calculated based on the responses of electrified households in the subjects' villages. Supply is measured using the available hours and nighttime hours, and the quality index is a binary composite statistic that accounts for supply, outages, and the frequency with which power voltages break grid equipment. Weak correlations between supply and willingness to pay (− 0.5 for both available and nighttime hours) and between the quality index and willingness to pay (− 0.001 using available hours and − 0.002 using nighttime hours) are not shown.

Table 1
Summary statistic comparison of villages on the basis of number of households with grid electricity. Unless otherwise noted, village-level data are categorized and then aggregated on the basis of the fraction of sampled households in the village that use grid electricity. The number of villages sum to 713, with one village excluded due to missing household-level electrification data. For sampled household size, monthly household expenditures, distance to the nearest statutory town, and village population, average values are provided across villages. Household expenditures are provided in Indian rupees and distance to the nearest town is in kilometers. Remaining figures (use of the grid, backward caste, and education) are presented as average proportions of village households with the given characteristic. Villages categorized as "all use" and "no use" are those in which no households or all households, respectively, use grid electricity. All observations used in the analysis come from "mixed use" villages, which are composed of households with and without grid electricity. Population and household data is obtained from the 2001 Census of India, and data on distance to the to the nearest statutory town is obtained from the 2011 Census of India.

Description	Mixed Use	All Use	No Use
Villages	547.00	125.00	41.00
Use Grid	0.63	1.00	0.00
Sampled Household Size	6.87	5.94	7.37
Backwards Caste	0.77	0.72	0.80
10th Year or Greater Education	0.37	0.40	0.34
Household Expenditure	5278.30	5510.93	4970.86
Household Expenditure (ln)	8.52	8.58	8.45
Kerosene Expenditure	73.89	28.38	106.32
Kerosene Expenditure (ln + 1)	3.95	2.51	4.46
Households	693.13	617.06	850.90
Households (ln)	6.07	6.00	6.21
Distance to Town	17.34	17.42	17.73
Distance to Town (ln + 1)	2.56	2.57	2.67
Village Population	3754.64	3000.35	4798.98
Village Population (ln)	7.76	7.57	7.93

Table 2
Summary statistic comparison of households on the basis of electrification. Unless otherwise noted, household-level data are categorized and then aggregated on the basis of whether or not the household uses grid electricity. One non-electrified household with missing data about willingness to pay is excluded from the sample. Available hours of electricity (out of 24) describe the total hours available to average households and the nighttime hours describe the hours of electricity available between sunset and midnight every day. Nighttime hours are used as a robustness check. The average village quality index is a binary scaled quality composite based on scaled available hours of electricity available, electricity outages, and days with broken equipment due to voltage fluctuations. Household expenditures on a monthly basis are provided in Indian rupees and distance to the nearest town is in kilometers. Population and household data are obtained from the 2001 Census of India, and data on distance to the to the nearest statutory town is obtained from the 2011 Census of India.

Description	Not Electrified	Electrified
Households	2348.00	4106.00
Households (ln)	7.76	8.32
Habitation Households	17.82	16.07
Habitation Households (ln)	2.02	2.01
Household Expenditure	4496.93	5736.70
Household Expenditure (ln)	8.25	8.45
Kerosene Expenditure	85.45	66.93
Kerosene Expenditure (ln + 1)	3.22	2.56
10th Year or Greater Education	0.27	0.42
Backwards Caste	0.83	0.73
Available Hours	9.70	11.50
Quality Index	0.75	0.78
Nighttime Hours	2.51	2.96

Table 3
Sample summary statistics. Unless otherwise noted, aggregation is conducted at the village-level across villages that exhibit variation in the proportion of households with electricity. Data on willingness to pay were only collected for non-electrified households, whose responses are aggregated at the village level unless otherwise noted. Habitation figures are calculated at the village-level based on a weighted average on the basis of the number of households in a given village that reside in a given habitation. Household-level statistics are for non-electrified households in villages where at least some households have access to grid electricity.

Variable	Minimum	Average	Maximum	Standard Deviation
Willingness to Pay	0.00	379.51	2000.00	309.30
Households	35.00	536.50	7000.00	640.43
Village Population	128.00	3739.11	34,715.00	4499.78
Household Size	0.39	9.43	316.66	17.63
Use Grid (Households)	0.00	0.60	1.30	0.28
Available Hours	1.00	10.84	23.00	4.91
Nighttime Hours	0.00	2.80	6.00	1.38
Quality (Available Hours)	0.19	0.77	0.99	0.10
Quality (Nighttime Hours)	0.24	0.72	0.93	0.09
Habitation Households	1.17	16.71	115.67	19.67
Habitation Population	7.92	118.45	825.75	144.06
Distance to Town	0.00	17.42	121.00	15.66
Electricity Costs	0.00	191.92	1962.50	158.89
Household Expenditure (Village Averages)	2125.00	5284.95	11,333.33	1665.81
Kerosene Expenditure (Villages Averages)	0.00	73.66	522.83	51.70
10th Year or Greater Education	0.00	0.37	0.92	0.19
Backwards Caste	0.00	0.77	1.00	0.23
Willingess to Pay (Household-Level)	0.00	398.72	3000.00	479.09
Household Expenditure (Household-Level)	500.00	4496.93	30,000.00	2987.10
Kerosene Expenditure (Household-Level)	0.00	85.45	3900.00	123.53
Household Size (Household-Level)	1.00	6.48	26.00	3.16

Table 4
OLS estimates of willingness to pay for those not currently receiving grid electricity. State fixed effects introduced in each model. Standard errors are clustered by village.

	(1)	(2)	(3)
Available Hours	−0.000		
	(0.015)		
Quality Index		0.351	
		(0.689)	
Nighttime Hours			0.010
			(0.063)
ln(Habitation Households)	−0.021	−0.021	−0.021
	(0.047)	(0.047)	(0.047)
ln(Distance to Town)	−0.053	−0.048	−0.052
	(0.077)	(0.078)	(0.078)
ln(Household Expenditure)	0.447***	0.450***	0.448***
	(0.101)	(0.101)	(0.101)
10th Year or Greater Education	0.274**	0.277**	0.275**
	(0.119)	(0.119)	(0.119)
Backwards Caste	−0.191	−0.196	−0.193
	(0.149)	(0.149)	(0.148)
ln(Kerosene Expenditure)	0.115*	0.113*	0.114*
	(0.064)	(0.064)	(0.064)
Constant	1.052	0.755	1.017
	(0.966)	(1.091)	(0.974)
Fixed effects: state	Yes	Yes	Yes
VCE	cluster	cluster	cluster
R-squared	0.068	0.068	0.068
Observations	2348	2348	2348

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

shown in Table 1.[13] The analysis in this study relied on villages in which some, but not all, households had access to grid electricity power, and as illustrated in the table, these “mixed-use” villages compose nearly 80% of the sample villages and total populations. The villages composed of households with and without grid connections are generally representative of the entire sample, though they tend to have somewhat lower rates of education and a greater average household size than their counterparts in which all households have grid connections.

Descriptive statistics summarizing differences between electrified and non-electrified households are provided in Table 2. Electrified households tend to be located in larger villages than non-electrified households but, as illustrated by the households per habitation for each group, they are not more concentrated than their counterparts. Unsurprisingly, they also tend to be wealthier than non-electrified households (Banerjee et al., 2014; Aklin et al., 2015) with higher rates of education and a lower proportion of scheduled caste population. Furthermore, villages in which electrified households reside tend to have better electricity service, as measured across a number of dimensions including supply, operationalized using total hours and nightly hours and the composite quality variable. Aside from the problem of selection, estimates of the relationship between quality — the explanatory variable in this analysis — and WTP may be biased, with confounding due to a number of characteristics summarized in Table 3 that share a common cause with both quality and WTP.

Table 3 also allows us to compare the current expenses of non-electrified households for kerosene to what they could receive for the same amount in electricity. The average non-electrified household reports expending 85.6 rupees per month on kerosene. Depending on how much is purchased from PDS versus on the market, this means they can purchase between 3.30 and 4.76 l a month, or about enough to power a

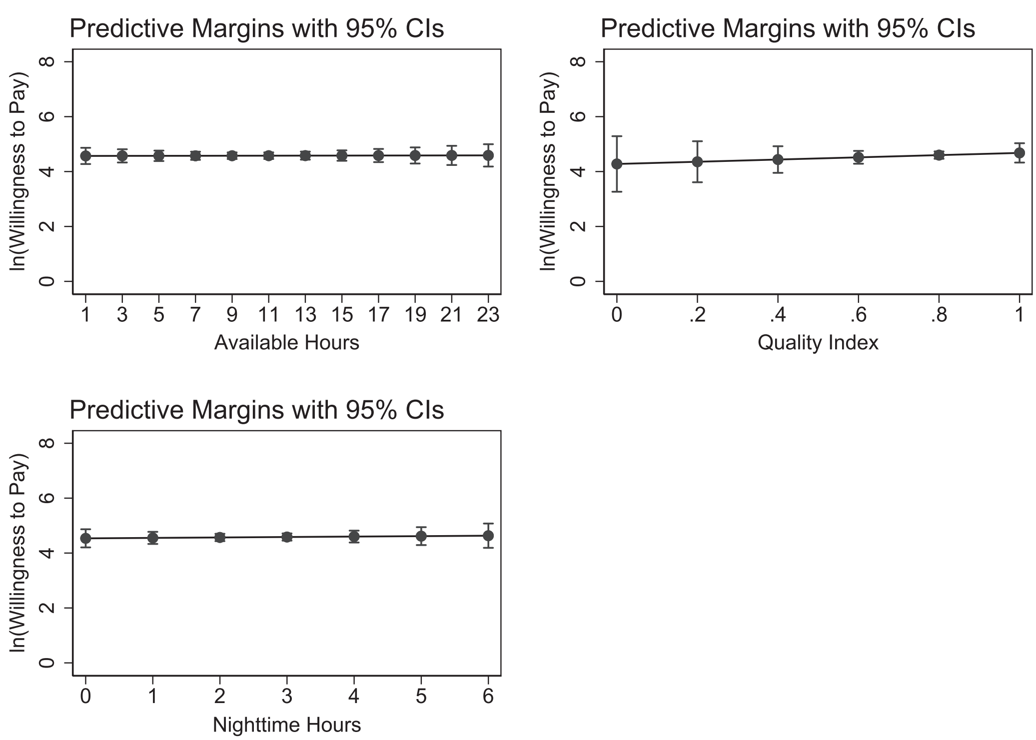

Fig. 2. Linear prediction and 95% confidence intervals for the effect of electricity reliability on willingness to pay based on OLS models from Table 4.

3.4. Control variables

Descriptive statistics summarizing differences between villages based on the variation in the number of households using power are

[13] Distributions of non-electrified villages' average and total habitation size, the total number of households in the habitation, and households' monthly expenditures are provided in Section A2.3.

Table 5
Heckman sample selection models (MLE) for willingness to pay, where first stage models the likelihood of not having a connection to grid electricity. State fixed effects introduced in each model. Standard errors are clustered by village.

	(1)	(2)	(3)
Outcome			
Available Hours	0.130***		
	(0.021)		
Quality Index		4.805***	
		(0.878)	
Nighttime Hours			0.338***
			(0.085)
ln(Distance to Town)	− 0.143	− 0.135	− 0.152
	(0.120)	(0.122)	(0.123)
ln(Household Expenditure)	1.512***	1.535***	1.538***
	(0.126)	(0.127)	(0.127)
10th Year or Greater Education	1.432***	1.443***	1.441***
	(0.139)	(0.139)	(0.141)
Backwards Caste	− 0.984***	− 0.952***	− 0.960***
	(0.179)	(0.182)	(0.179)
ln(Kerosene Expenditure)	− 0.252***	− 0.254***	− 0.262***
	(0.078)	(0.078)	(0.081)
Constant	− 4.378***	− 6.907***	− 4.065***
	(1.212)	(1.404)	(1.229)
Selection			
Available Hours	− 0.038***		
	(0.006)		
Quality Index		− 1.386***	
		(0.234)	
Nighttime Hours			− 0.093***
			(0.022)
ln(Habitation Households)	− 0.009	− 0.010*	− 0.010*
	(0.006)	(0.006)	(0.006)
ln(Distance to Town)	0.048	0.046	0.051
	(0.031)	(0.032)	(0.032)
ln(Household Expenditure)	− 0.378***	− 0.382***	− 0.381***
	(0.032)	(0.032)	(0.032)
10th Year or Greater Education	− 0.357***	− 0.364***	− 0.361***
	(0.036)	(0.036)	(0.036)
Backwards Caste	0.248***	0.238***	0.237***
	(0.045)	(0.046)	(0.045)
ln(Kerosene Expenditure)	0.089***	0.089***	0.092***
	(0.020)	(0.020)	(0.020)
Constant	2.826***	3.529***	2.686***
	(0.323)	(0.374)	(0.325)
$atanh(\rho)$	− 3.172***	− 3.174***	− 3.182***
	(0.092)	(0.087)	(0.086)
$ln(\sigma)$	1.357***	1.358***	1.361***
	(0.024)	(0.024)	(0.024)
Fixed effects: state	Yes	Yes	Yes
VCE	cluster	cluster	cluster
N	6454	6454	6454

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

37-lumen kerosene lamp for about 4–6 h per day. A small, 3-watt LED light would offer over 200 lumens at absolutely minimal electricity consumption. This comparison suggests that there are substantial efficiency gains to be had by switching to electricity for lighting: with modern technology, the amount of energy consumed for basic lighting is negligible. In Uttar Pradesh, for example, the 2017–2018 tariff order specified an 80-rupee fixed charge an additional cost of only 3 rupees per kilowatt-hour for households consuming fewer than 100 kilowatt-hours per month (UPERC, 2017).

To avoid confounding, we control for the number of households in the villages' habitation, their distance from the nearest town, households' monthly expenditures, their education, their scheduled caste/tribe status, and their monthly expenditure on kerosene. The number of households in a village's habitation is used to operationalize the concentration of households, which predicts the local electricity distribution system (Chaurey and Kandpal, 2010), associated costs (Sinha et al., 1991; Abdullah and Jeanty, 2009), and the marginal effects from electrification (Mellor, 2014). We control for distance to the nearest town, which is a strong predictor of electrification in a number of countries including India (Oda and Tsujita, 2011; Blum et al., 2013; Dugoua et al., 2017), and is associated with reliability and interruption costs (Harish et al., 2014). We also include state fixed-effects to account for items such as state-wide quality of grid infrastructure.

The quality of grid infrastructure is capital intensive and to receive high quality electricity, customers must pay higher fees (D'Agostino et al., 2016). A number of studies (Winkler et al., 2011; Alkon et al., 2016; Dugoua et al., 2017) have found relationships between income and the quality of electricity. This aligns with findings by Urpelainen and Yoon (2017), demonstrating the relationship between the rate of technological adoption and credit constraints. To avoid confounding on the basis of income, which would affect both households' WTP and the quality of their electricity, we control for it using households' monthly expenditures, which is a common proxy.

Additionally, we control for individuals' education, distinguishing them on the basis of whether they have completed their 10th year of education. Education, like income, predicts households' awareness of technological products (Urpelainen and Yoon, 2015) and their willingness to pay for them (McEachern and Hanson, 2008; Rebane and Bradford, 2011; Lay et al., 2013). For similar reasons, we control for caste and tribe, significant determinants of electrification in the region (Dugoua et al., 2017). We distinguish household heads who are members either of scheduled castes, scheduled tribes, or backward classes from others using the variable Backward Caste. The Government of India formally recognizes scheduled castes and tribes and other backward classes as historically disadvantaged groups, enumerating them in its constitution.

4. Results

To begin this section, we look at the standard OLS estimates of WTP without modeling the selection into electrification. Table 4 shows the results of this estimation. Model 1 uses total available hours of electricity to determine WTP, Model 2 uses our quality index, and Model 3 looks at reported nighttime hours of electricity. In all three of the models, the result is the same. While the effect of electricity quality has a positive influence on WTP, the error of the estimates is large, and none of them reach standard levels of statistical significance. This can be seen in more detail in Fig. 2. The overall effect of electricity quality is relatively flat with large error bounds.

Several other auxiliary findings from Table 4 also merit attention. As expected, those households with higher household expenditures are more likely to be willing to pay for electrification. Similarly, those households where the head of the household has achieved 10 years or more of education are more likely to be willing to pay. It is also important to note that the natural log of households in the habitation does not significantly affect WTP, making it a good candidate for our instrumental variable.

In Table 5, we estimate the selection feature for a household being electrified and include the Heckman correction in the outcome equation. The results here are very different. In all three models, the quality measures are highly significant ($p < 0.01$) and suggestive of a substantial positive relationship between quality and WTP. For the total number of hours available, a 1 h increase in availability increases the WTP by about 13%. Similarly, moving up the quality scale by 1/10 of a point (the scale ranges from 0 to 1) increases WTP by about 48%. Finally, a 1 h increase in nighttime hours increases WTP by about 34%. Fig. 3 shows these effects visually and demonstrates the significant difference in WTP across quality measures. Placing these percent

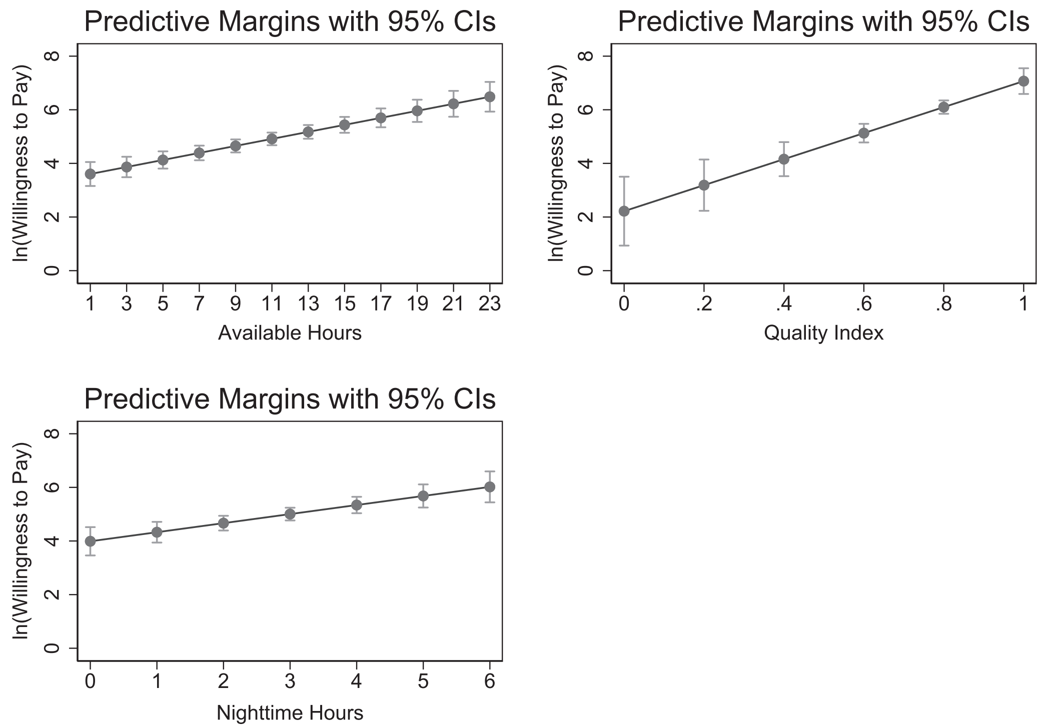

Fig. 3. Linear prediction and 95% confidence intervals for the effect of electricity reliability on willingness to pay based on sample selection models from Table 5.

increases into monetary form, the average non-electrified household reports being willing to pay 399 rupees (USD 6.18). A 1 h increase in total hours available would increase this by about 52 rupees (USD 0.81). A 1/10 point increase in the quality scale would increase this by about 192 rupees (USD 3.00). Similarly, a 1 h increase in nighttime hours would increase WTP by about 136 rupees (USD 2.12).

In addition to the main findings, there are also some interesting ancillary findings within the control variables. For example, while being a member of a backwards caste increases the probability of having an electricity connection, members of these casts have a lower WTP. This can largely be explained by the subsidization that takes place for electrical connections, lowering the costs, and therefore WTP, for members of backwards castes. This relationship was not captured in the OLS regression model that did not model the selection process.

Finally, the results of the model parameters $atanh(\rho)$ and $ln(\sigma)$ are both statistically significant, indicating that selection is a significant issue in the OLS models. A Wald test of independent equations (H_0: $\rho = 0$) rejects the null hypothesis that this process could be modeled through a separate probit and OLS model produces χ^2 scores of 1195.64, 1321.29, and 1364.08 respectively. All easily rejecting the null hypothesis ($p < 0.0001$).[14] Moreover, while it is always risky to interpret ρ substantively, the negative direction is also consistent with our understanding of the selection process – those with higher willingness to pay are less likely to remain unelectrified.

In sum, the results suggest a substantial role for quality in determining willingness to pay once the selection process is taken into account. Regardless of how we measure the quality of electricity, we see a robust association between the quality of electricity service in the community and WTP. This robust association is, however, only observed when we correct for the selection bias.

[14] While the number of households in habitation does not independently reach conventional levels of statistical significance, a likelihood-ratio test of the probit models suggests the addition of this variable significantly changes the model at conventional levels ($p < 0.05$).

5. Conclusion

Using data from rural India, we have confirmed the importance of high-quality service for households' willingness to pay for electrification. The results show that this association is robust: in communities where daily hours of electricity availability are high and outages or voltage fluctuation rare, households are willing to pay higher amounts even when controlling for other determinants such as household expenditure, educational attainment, and caste status.

Our first important contribution is methodological. By applying the Heckman (1979) selection model, we have corrected for the bias stemming from the fact that survey-measured WTP for electrification is meaningless for already electrified households. As we demonstrate, the correction has a substantial impact on the results: the quality of electricity service, and nighttime hours in particular, have a large and robust effect on WTP. In the models that fail to correct for sample selection, this important result disappears because of selection bias.

The policy implication is clear: improving the quality of service is essential. India's problems with rural electricity service stem from the electricity distribution companies' poor financial performance (Santhakumar, 2008; Joseph, 2010), and our results show that improving the quality of service would allow distribution companies to connect more households and charge cost-recovering prices for electricity. Improvements in the quality of service would increase households' WTP for the service, and the revenue for prices that cover the real cost of generating, transmitting, and distributing electricity would in turn help pay for those improvements.

India's recent rural electrification efforts (Palit and Bandyopadhyay, 2017) have neither emphasized service quality nor tried to target communities with high WTP. As household electrification continues to expand in the country, our results highlight the need to focus on service quality and the value of electricity service, as opposed to increased connectivity alone. As improving the quality of service increases WTP, then Indian policymakers may have a solution to the financial problems that rural electrification creates under heavily subsidized electricity prices. Creating such a strong link would depend on the government's ability to demonstrate that it is trustworthy, and uses revenue generated from higher prices to improve service quality.

The robustness of our results against different measures of quality is also important. While past work has found the hours of electricity to be a robust predictor of subjective satisfaction with lighting and electricity service (Aklin et al., 2016), we find that adequate community-level hours of supply *at night*, when rural households need domestic electricity the most, are strongly associated with WTP among non-electrified households. When we consider other dimensions of quality, we find the same robust association. Our results thus offer a comprehensive, encompassing approach to measuring the quality of rural electricity service in developing countries. This approach can inform efforts such that the World Bank's Global Tracking Framework (World Bank, 2017) to establish the quality of energy access across the world and over time. Future research should, in our view, continue to pursue this line of inquiry by considering the implications of service quality more broadly. Outcomes of interest might include appliance ownership and use, productive uses of energy, electricity theft, and non-payment rates. Another relevant direction for research would be to consider the role of service quality in distributed energy services, as our focus was on grid-supplied electricity.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2019.01.034.

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