Energy Strategy Reviews 21 (2018) 130–136

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

An evaluation of dynamic electricity pricing for solar micro-grids in rural India

Sini Numminen[a], Semee Yoon[b], Johannes Urpelainen[c,*], Peter Lund[a]

[a] School of Science, Aalto University. Finland
[b] Underwood International College and Graduate School of International Studies, Yonsei University, South Korea
[c] Prince Sultan bin Abdulaziz Professor of Energy, Resources and Environment, Postal code: 1619 Massachusetts Avenue, NW, Washington, DC, 22209, USA

ARTICLE INFO

Keywords:
Energy access
Solar power
Demand management
India

ABSTRACT

Stand-alone photovoltaic systems provide a potentially sustainable option for rural electrification, but the design and management of these systems is a challenge. Here we examine the ability of dynamic (real-time) pricing in off-grid systems to improve the durability of the batteries used to store power. In a randomized controlled trial with a pre-paid solar micro-grid in rural India, we found that dynamic pricing did not improve technical performance or customer satisfaction. The best explanation for the null finding is that, for various reasons, households minimized their power consumption and there was thus little need for demand management. These findings suggest that the low demand for power is a key challenge for the profitability of pre-paid off-grid systems.

1. Introduction

More than one billion people worldwide still lack access to electricity at home [10]. As a result, basic energy services such as household lighting or mobile charging in developing countries are often based on expensive and polluting alternatives such as kerosene or fuel generators. In these countries, stand-alone photovoltaic systems provide a potentially sustainable option for rural electrification [2]. The design and management of these systems, however, presents considerable challenges. A typical village solar power system consists of PV panels, a battery, DC-grid, and balance-of-system components. The battery is often technically and economically the most critical component, and may limit the availability of electricity delivered and lifetime of the whole system. Thus, techno-economic measures to protect batteries could play an important role in improving the performance and long-term viability of off-grid systems.

Here we investigate whether demand side management is effective in protecting the battery from deep discharge and thus improve the performance of solar photovoltaic systems. In a randomized controlled trial, we applied dynamic pricing to seven solar micro-grids [1,6,7,11] in rural Uttar Pradesh, India. By randomizing the presence or absence of dynamic pricing over a full year, we assessed whether the demand response to variation in the price of electricity could be used to improve the performance of the system. Under dynamic pricing (treatment condition), when the battery voltage decreased, the price of electricity went up to reduce consumption. Under static pricing (control condition), the price of electricity remained constant regardless of the battery voltage. This pattern, we hypothesized, would shift electricity consumption over time in a way that would improve battery life. The possible benefits of dynamic pricing would include longer battery life, more efficient use of electricity generation capacity, less need to invest in expensive oversized systems to deal with peak demand, and a more reliable supply of power to rural households. These benefits would, in turn, enhance consumer experience with stand-alone photovoltaic systems.

We did not find evidence for the effectiveness of dynamic pricing. Both the technical performance and the consumers' perceptions remained failed to improve under dynamic pricing, and there was even suggestive evidence that some consumers found the price changes irritating. The best explanation for this null result is that households minimized their power consumption and thus there was no need for demand management. As detailed below, households were very conservative in their power use, and technical problems further decreased their ability to benefit from electricity access. These results suggest that pay-*as*-you-go models may face challenges in generating enough revenue, as households respond to these models by being frugal with power use. Our experimental results show that in the absence of sufficient power demand, the benefits of dynamic pricing can be limited.

* Corresponding author.
E-mail addresses: sini.numminen@aalto.fi (S. Numminen), yoonsemee@yonsei.ac.kr (S. Yoon), JohannesU@jhu.edu (J. Urpelainen), peter.lund@aalto.fi (P. Lund).

https://doi.org/10.1016/j.esr.2018.05.007
Received 20 November 2017; Received in revised form 11 March 2018; Accepted 31 May 2018
Available online 13 July 2018

2. Dynamic pricing in rural off-grid electrification

Stand-alone photovoltaics typically consist of solar PV modules, a battery unit for energy storage, and necessary balance of system components to enable a functioning system. With declining costs of solar panels, the cost of the battery plays an increasing role of the total costs, also its life-time is much shorter than that of the PV panels. Therefore, to avoid oversizing, drainage of battery, and reduced lifetime, demand side management (DSM) could play an important role in off-grid systems.

When the price of electricity depends on the battery status under dynamic pricing, households have incentives to reduce their consumption when the battery discharge approaches potentially harmful levels. In practice, households have incentives to avoid high prices at night, when (i) the demand for electricity in the habitation is high because members of different households are at home and need lighting and (ii) the sun is not shining, so that the battery must discharge. If dynamic pricing prevents deep discharge and encourages households to use electricity when the sun is shining, then the likelihood of blackouts, brownouts, and voltage fluctuation should decrease. Avoiding discharges also protects the battery from degradation. Unfortunately, the benefits of dynamic pricing for off-grid solar systems have not been estimated in previous studies, perhaps due to factors such as the small power quantities involved per system and full power autonomy of such systems. The control of off-grid solar systems typically just concerns the battery management, whereas the consumers are not included in the power management.

Previous studies on consumers in electricity markets of industrialized countries indicate that dynamic pricing of retail electricity can lead to major gains [4,12], whereas the question would a consumer adopt dynamic pricing in practice and change behavior contributing to power consumption flexibility remains somewhat open [3]. Active consumer participation has been recognized as a critical question for future demand response [9]. Faruqui and Sergici [8] analyzed 15 recent pilots and full-scale implementations of dynamic pricing of electricity and found conclusive evidence that households respond to higher prices by lowering usage. However, the magnitude of price response depends on several factors, such as the magnitude of the price increase and the consumer-technology communication interface.

3. Data and methods

In our experiment, we installed seven solar microgrids in seven habitations in the Unnao district of the state of Uttar Pradesh in India. All households were non-electrified before and during the study period (52 weeks), except for the use of the solar microgrid. The solar microgrids in our intervention were low-voltage direct current (DC) distribution grids delivering power to 5–7 households each. Customers could use small electronic appliances with a maximum instantaneous peak load of 30 W. In practice, households were able to use three LED lights, a fan, and a socket for charging mobile phones and small appliances. Batteries were used to store solar power for use at night, and the battery cost was approximately 10–15% of total system cost. The batteries were sized such that they could power households' maximal use – lights, mobile charging, and fan – for 12.5 h and lights only for 22.5 h even without any insolation. The most important seasons for battery use and risk of discharge were the monsoon and the December–January fog. See data and methods appendix for full system details.

The treatment was randomly assigned on a weekly basis at the habitation level, so that each habitation was in the control and treatment condition at different times over the study period. All households within a habitation were in the same condition in any given week. In the static pricing mode (control), the price of electricity was fixed and did not vary over time. In the dynamic pricing mode (treatment), the price varied depending on the status of the battery. When the voltage of the battery descended below or ascended over a particular limit, the central power station sent a signal to the energy meters in the households to change the price of electricity. This system encouraged households to use more (less) electricity when the battery charge was high (low). Overall, the treatment assignment was successful. Based on a comparison of the price recorded on the central charging station data and the randomization scheme, 93.5% of the data collected through the central charging station at each habitation showed the correct pricing. Deviations were caused by human (e.g., accidentally setting the incorrect pricing condition) and technical errors (e.g., energy monitors not responding to the enumerators' instructions). When dynamic pricing was applied, the price was low 88% of the time and high only 3% of the time. This imbalance indicates that the households were very conservative with electricity use.

To assess the value of dynamic pricing, we test the following hypotheses:

1. **Efficiency**: Relative to the static mode, in dynamic mode households consume less electricity.
2. **Performance**: Relative to the static mode, in dynamic mode households experience fewer technical problems.
3. **Customer Experience**: Relative to the static mode, in dynamic mode households improve customer satisfaction.
4. **Battery Protection**: Relative to the static mode, in dynamic mode the self-consumption index (see data and methods) is higher.

We report results from linear regression models on the outcomes discussed above. The statistical modeling is used to derive estimates of the causal impact of dynamic pricing from the experimental data. The estimation equation can be written as:

$$Y_{ijt} = \alpha_i + \beta_t + T_{jt} + \varepsilon_{ijt}, \tag{1}$$

where i indexes households, j habitations, and t weeks. Y is the outcome variable, T is the treatment indicator (dynamic pricing), α and β are fixed effects, and ε is the error term. The unit of analysis is a household-week, that is, each row of the data consists of variable values for a specific household during one week over the study period. All regressions include household and week fixed effects, meaning that we estimate the effect of changes in treatment status (static versus dynamic pricing) on changes in outcomes (e.g., electricity consumption) within a household while controlling for common temporal trends over the study period. Standard errors are clustered by habitation-week, the level of treatment assignment, to account for correlation across households' treatment status within any given habitation at a given time.

The independent variable of interest is the assignment to dynamic pricing. We estimate intent-to-treat (ITT) effects, so that the focus is on the effects of the intended (i.e., randomized) pricing mode. This is conservative estimate of the treatment effect because we may sometimes fail to achieve the intended pricing mode because of technical issues or human error. In practice, however, given the very high association (0.935) between assignment and realization of treatment, this specification choice is innocuous. In Supporting Information (SI), Table SI S1 shows balance statistics, summarizing the information collected on a weekly basis into the control group (static pricing) and the treatment group (dynamic pricing). As the table shows, the randomization across households was successful, with only two of the 23 covariates having a statistically significant difference. Outcomes are summarized by treatment condition in SI Table S2 and household characteristics collected in the baseline surveys prior to the introduction of the dynamic pricing scheme are described in SI Table S3.

The dependent variables are defined as follows:

- Table 1: weekly actual use of electricity in watt-hours (energy meters); the number of hours households used electricity for lighting, fans, and mobile phone charging (surveys).

Table 1
Effect of dynamic pricing on electricity consumption and use. The unit of analysis is a household-week. The models are linear regressions and the dependent variables are the weekly actual use of electricity (watt-hours) and the number of hours during which households used electricity for lighting, fans, and mobile phone charging. FE refers to inclusion (yes) or exclusion (no) of fixed effects.

	Watt-hour		Light hrs		Fan hrs		Mobile hrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dynamic Pricing (ITT)	−6.017	0.742	−0.096**	−0.081**	0.003	0.000	−0.009	−0.013
	(4.754)	(4.051)	(0.044)	(0.037)	(0.022)	(0.017)	(0.015)	(0.012)
Habitation FE	No	Yes	No	Yes	No	Yes	No	Yes
Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.001	0.085	0.003	0.093	−0.000	0.153	−0.000	0.113
Observations	1950	1950	2232	2232	2232	2232	2232	2232
Mean of Dep Var	107.212	107.212	2.452	2.452	0.098	0.098	0.156	0.156

Standard errors clustered by habitation-week in parentheses.
$^{*}p < 0.10$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

Table 2
Effect of dynamic pricing on self-reported technical problems. The unit of analysis is a household-week. The models are linear regressions and the dependent variables are the number of problems households had charging light bulbs, fans, and mobile phones each week.

	Light Problems		Fan Problems		Mobile Problems	
	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic Pricing (ITT)	0.438*	0.544***	0.077	0.059	0.046	0.058*
	(0.246)	(0.196)	(0.057)	(0.046)	(0.032)	(0.031)
Habitation FE	No	Yes	No	Yes	No	Yes
Week FE	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.004	0.215	0.001	0.136	0.002	0.050
Observations	2232	2232	2232	2232	2232	2232
Mean of Dep Var	1.302	1.302	0.151	0.151	0.057	0.057

Standard errors clustered by habitation-week in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

- Table 2: number of problems households had with using light bulbs, fans, and mobile phones each week (surveys).
- Table 3: households' perception of electricity price (1 very expensive to 5 very cheap), difficult to use the pre-paid system (1 very difficult to 5 very easy), and satisfaction with the provider Boond's service (1 very unsatisfied to 5 very satisfied).
- Table 4: daily self-consumption index (0–1, with higher values indicating more direct use of sunlight), calculated following Luthander et al. [13].

4. Effects of dynamic pricing

The effects of dynamic pricing on electricity consumption are reported in Table 1. In Models 1–2, the outcome variable is the total consumption of electricity in watt-hours. Models 2–8, in turn, show the result for self-reported use of electricity for lighting, fan, and mobile charging in hours. Overall, the effect of dynamic pricing is relatively weak. Variation in the price of electricity seems to have a very small negative effect of about one-tenth of an hour on self-reported lighting hours per week, but for all other outcomes the confidence bounds are wide relative to the small coefficients.

The result on electricity consumption in watt-hours is further illustrated in Fig. 1. The figure shows that there is considerable seasonal variation in watt-hour consumption, with consumption peaking in the hot season (April–May), but there is no clear pattern of difference between households in dynamic versus static pricing in any given week. This is consistent with the weak results from the regression analysis above on watt-hour consumption.

Table 3
Effect of dynamic pricing on subjective satisfaction. The unit of analysis is a household-week. The models are linear regressions and the dependent variables are households' perception of electricity price (1 very expensive to 5 very cheap), difficult to use the pre-paid system (1 very difficult to 5 very easy), and satisfaction with the provider Boond's service (1 very unsatisfied to 5 very satisfied).

	Electricity Price		Difficulty		Satisfaction	
	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic Pricing (ITT)	−0.093*	−0.054	−0.040	−0.023	−0.030	−0.092
	(0.050)	(0.043)	(0.039)	(0.027)	(0.102)	(0.084)
Habitation FE	No	Yes	No	Yes	No	Yes
Week FE	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.002	0.085	0.000	0.166	−0.000	0.226
Observations	2231	2231	2232	2232	2232	2232
Mean of Dep Var	2.993	2.993	4.591	4.591	4.239	4.239

Standard errors clustered by habitation-week in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Effect of dynamic pricing on the self-consumption index. The unit of analysis is a habitation-week. The models are linear regressions and the dependent variable is the self-consumption index (0–1).

	SC -24h		SC	
	(1)	(2)	(3)	(4)
Dynamic Pricing (ITT)	−0.021	−0.028**	−0.009	−0.007
	(0.016)	(0.013)	(0.015)	(0.010)
Habitation FE	No	Yes	No	Yes
Week FE	No	Yes	No	Yes
Adjusted R^2	0.003	0.405	−0.002	0.451
Observations	270	270	270	270
Mean of Dep Var	0.394	0.394	0.137	0.137
St. Dev of Dep Var	0.131	0.131	0.115	0.115
Min of Dep Var	0.099	0.099	0.001	0.001
Max of Dep Var	1.000	1.000	1.172	1.172

Standard errors clustered by habitation-week in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2, in turn, shows the results for self-reported technical problems. The dependent variables are counts of self-reported problems per week. Interestingly, here we see modest evidence of the dynamic

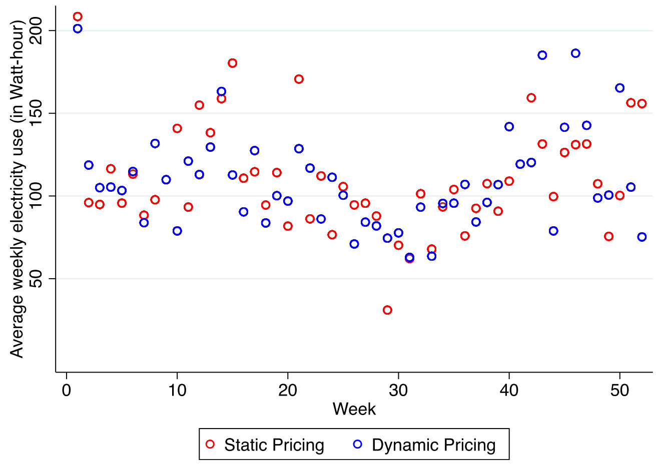

Fig. 1. Average weekly watt-hours by treatment. The red dots represent the average weekly watt-hours for households under static pricing in each week, and the blue dots represent the same of households under the dynamic pricing scheme.

pricing worsening self-reported problems with lighting. In the dynamic pricing mode, the weekly count of problems with lighting increases by 0.4–0.5 relatively to the static pricing mode. The coefficients for the other problems, on the other hand, are small and statistically insignificant with one exception (model 4, mobile problems). These results suggest that under dynamic pricing, there were more problems with power availability and power quality, and the respondents perceived these when lights went out.

Next, we turn our attention to customer satisfaction. The results are shown in Models 1–6 of Table 3. The outcome variable is subjective satisfaction on a 1–5 scale, with higher values indicating more satisfaction. Again, we see that dynamic pricing has a negative effect on satisfaction with the electricity price. It seems that the variation in the price disturbs the households even though the intention is to protect the system from damage and improve its durability. Perceived difficulty of use and the quality of Boond's service, on the other hand, do not change.

Finally, Table 4 shows how the self-consumption index – energy consumed directly from the sun without battery storage (see data and methods for details) – changes with dynamic pricing. The unit of analysis is a habitation-week because self-consumption is defined for the central controlled at the habitation level. Models 1–2 show the results for self consumption over each 24-h period, so that night times without any power consumption are considered in the calculation; models 3–4 focus on times when power is actually being produced. Here we see little evidence of changes: dynamic pricing seems not to have increased the self-consumption index at all, with slightly negative coefficients that are statistically indistinguishable from zero, except for one model. Most importantly, the coefficients are small and statistically insignificant in models 3–4 that exclude times when power is not produced.

Overall, the results offer little evidence for the benefits of dynamic pricing. Neither technical performance nor consumer satisfaction improved. We consider the best explanation for this null finding to be the minimal demand of power among the consumers. With a weekly watt-hour power use of only 110 under dynamic pricing (104 under static pricing), the households only used minimal amounts of electricity for lighting and mobile charging, with minimal use of the fan: the average daily hours of fan use was only 0.097 h among the households under study. Besides the relatively high cost of running a fan, this lack of use could also reflect problems with the fans that Boond supplied, as we sometimes observed faulty products and difficulties with connecting the fans to the electricity sockets. In such circumstances, power demand was minimal most of the time. Even under dynamic pricing, the price of electricity remained in the low mode 88% of the time, as noted above. If demand-side management had been an issue, we should have seen frequent switches to medium and high prices.

Furthermore, power outages due to technical problems may have curtailed energy use even further: while power outages were indistinguishable between the static and dynamic pricing modes, the number of minor interruptions or data transmission problems was higher during dynamic pricing (SI Table S7). Although the minor interruptions were not common enough to explain the low power consumption, they may have amplified households' general unwillingness to pay for relatively large loads of power to operate the fan. Finally, we found some qualitative evidence that households were irritated when the price increased under dynamic pricing, as households complained in the interviews about the price increases. Household heads told us that they found the high prices irritating, a problem that may have been amplified by the fact that the high price was sometimes followed by a power outage, as per the design of the dynamic pricing system.

5. Conclusion

The above experimental results underscore the limitations of dynamic pricing as a method of demand-side management in off-grid systems. In our study, dynamic pricing did not protect the battery of the system from deep discharge because electricity demand in general was quite low. Similar to earlier research [7], households used the pre-paid system to minimize their power consumption, mostly using electricity for lighting and mobile charging. Although the results are less robust, we also found some evidence that the dynamic pricing method caused problems with electricity flow and pricing data, resulting in irritation among households. Most of these problems were relatively minor interruptions or data transmission problems, however, as actual outages did not increase in the dynamic condition based on our technical data (SI Table S7).

To be sure, our research design has its limitations. We have randomized dynamic pricing by week, which is not a realistic pricing strategy. By allowing the price to vary from week to week, we may have contributed to some confusion among the subjects, as they may have anchored their expectations to the lower prices, which are typical of the local off-grid market. Studies of different dynamic pricing strategies in larger samples with commercially viable pricing strategies are, therefore, a natural avenue for future research. Another notable limitation is our focus on relatively small pico-grids that only offer lighting and air circulation. In larger systems that power cooling and productive uses, dynamic pricing might prove more useful, as the peak load would be much larger.

The key implication of these findings for the growing off-grid industry is the importance – and difficulty – of estimating power demand in advance. When the system has a large capacity relative to demand, dynamic pricing and other sophisticated demand-side management are costly but not necessary. In our study, the low demand for power meant that even under dynamic pricing the price of power rarely increased beyond the baseline level. Dynamic pricing might have been more useful if households had been willing and able to pay for the use of electric fans, televisions, and other technologies that consume much more energy than lighting and mobile charging. The primary challenge for off-grid entrepreneurs, then, remains identifying and creating demand for energy. Only under a scenario of relatively high power demand will techniques such as dynamic pricing become relevant.

5.1. Data and methods appendix

This section offers additional detail on the data and methods used. A pre-analysis plan for the data analysis is available at http://egap.org/registration/1662. By specifying the estimation strategy in advance, the pre-analysis plan reduces the risk of bias from multiple comparisons and selective reporting of findings [5].

5.2. System specification

The solar microgrids were assembled and installed by Boond Engineering and Development, an Indian energy service company [14]. The systems were sized based on previous experience with similar systems in the Unnao area under the assumption that households would use electricity for mobile charging, lighting, and fans.

The power is supplied by two 100 W solar PV panels that charges a 120 Ah lead-acid battery bank. The energy is fed to the grid by a central charging station – at the habitation level – with a 24 V distribution voltage. Direct current (DC) distribution had been chosen for its energy efficiency: conversion to AC from the direct current PV power is thus avoided. Solar panels are mounted to an optimal angle of 23°. Boond technicians control the status of the battery bank and take care of the maintenance of the technical equipment. The local system operators are advised to clean the PV panels weekly.

The central charging station senses the voltage of the battery bank and sends the price information to the households via a separate serial data cable. The minimum voltage values for different energy prices were chosen as to protect the battery from deep discharge. High price: 21.6 V (21.6. V); Medium price: 23.5 (23 V); Low price: 24.5 V (24 V). In brackets are the values if the solar charging is zero. After the cut-off at 21.6 V, the central charging station feeds power again to the grid only when the voltage once exceeds 25.6 V.

The households are equipped with three LED light bulbs, a fan, and a socket for using small personal electronic appliances. Households can monitor their energy consumption in the energy meters. The customers have 24/7 power availability but the maximum power consumption at any given time is 30 W. The households pay for electricity according to the experimental specifications. In practice, a household buys credit from the local system operator in advance (pay as you go) and uploads them into the energy meter within the household. This is a pre-paid system that allows households to control their electricity consumption. When the credit runs out, power is disconnected unless the customer purchases more.

Technical details of the system components:

- PV panels: Two Alpex Solar 'Alpex 12100 100 W' panels. Application class: A. Open-circuit voltage 21 V, short-circuit current 6.15 A.
- Battery bank: Two Tubular type lead-acid batteries Artheon Black EON 60 T 'Premium Quality Solar Battery'. 12 V, 60 Ah each.
- Central charging station: Manufacturer EmSys Electronics. Output: 24 V DC. Short circuit protection, over load protection, low-voltage cut-off and high voltage cut-off. Data logging.
- Energy meter: Manufacturer: EmSys Electronics. Input 24 V DC. Output 12 V DC.
- Communication: Serial communication and a separate data cable, baud rate 9600 bps (RS-485).

The system is illustrated in Fig. 2 and an actual household energy meter shown in Fig. 3.

5.3. Treatment variable

The treatment variable was randomly assigned at the habitation-week level. The control condition was static pricing: the price of electricity was set at INR 10 per 100 W-hours.

The treatment condition was dynamic pricing: in this condition, the price varied depending on the battery condition. When the voltage of the battery descended below or ascended over a particular limit, the central power station sent a signal to the energy meters in the households to change the price of electricity. In the low price mode (green light), the price is INR 10 per 100 W-hours. In the medium price mode (yellow light), the price is INR 15 per 100 W-hours. In the high price mode (red light), the price is INR 20 per 100 W-hours. These prices were chosen by Boond in collaboration with the research team. INR 10–15 is the standard price range used by Boond, whereas INR 20 reflects a sufficient increase to deter excessive power consumption without being so high as to make electricity prohibitively expensive. In practice, the prices appear to have been low enough to encourage rapid

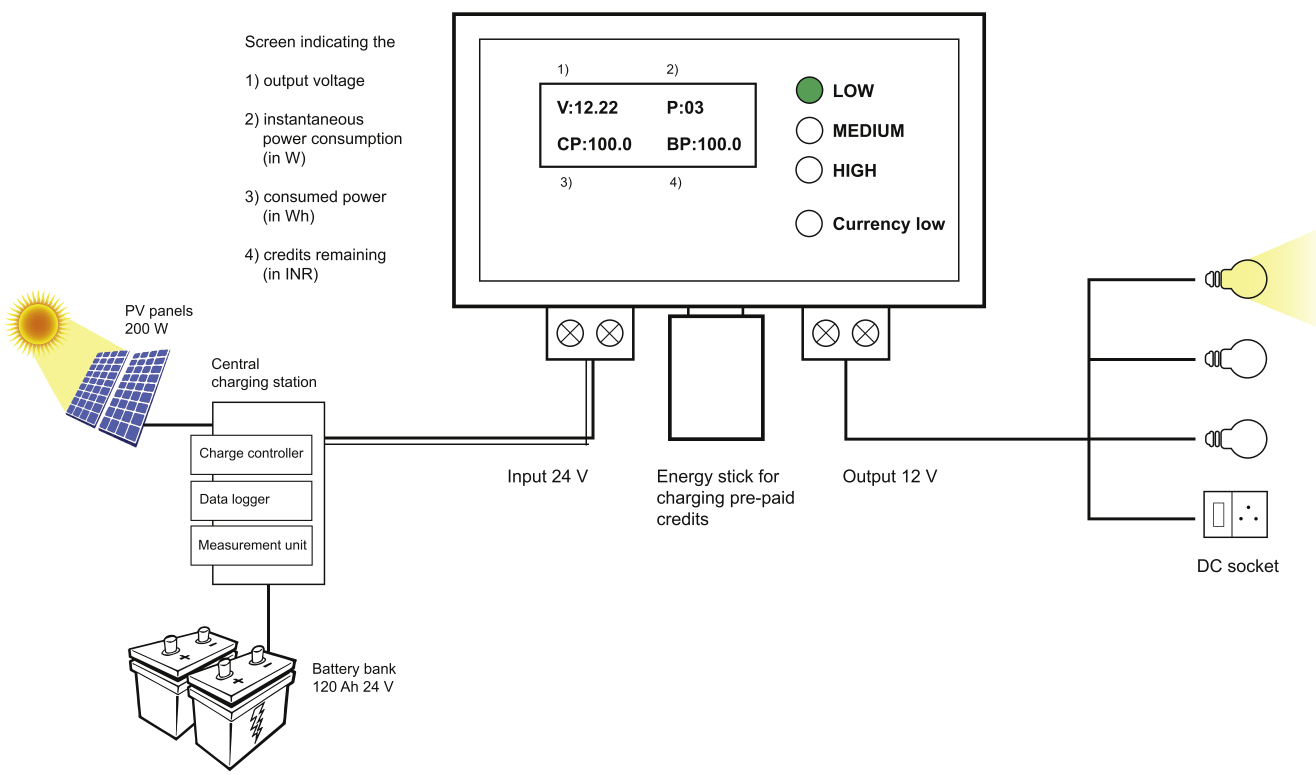

Fig. 2. Design of the smart energy meter and the solar pico-grid.

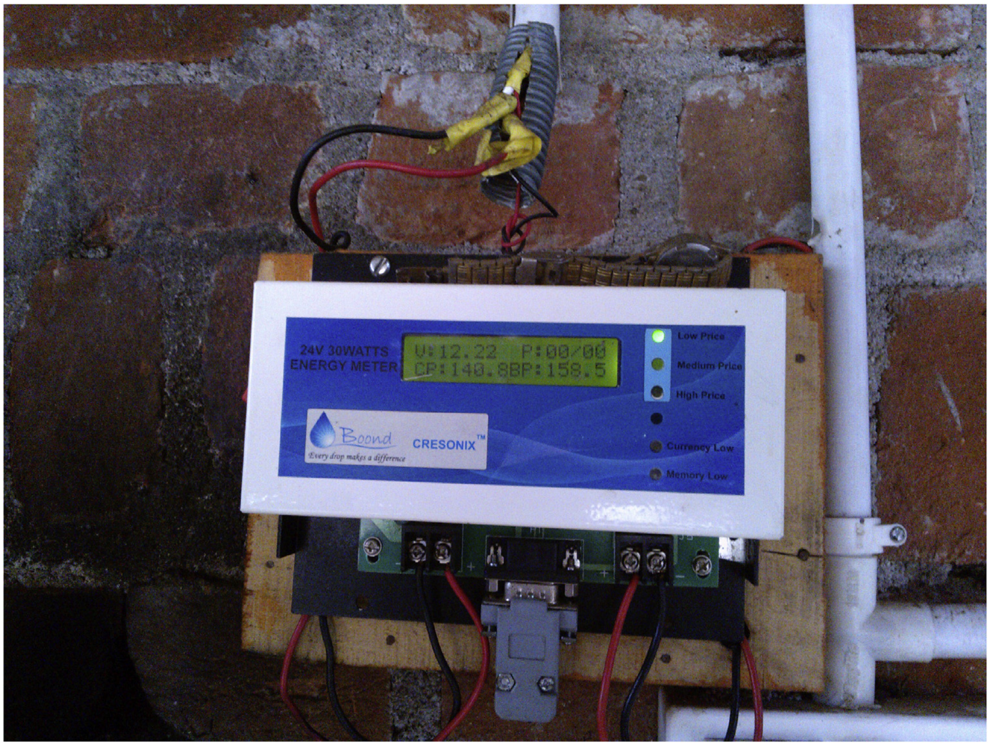

Fig. 3. A household energy meter, with electricity price set to the lowest level. The three lights (green, yellow, red) in the upper-right corner indicate the current electricity price. The lights in the lower-right corner, in turn, indicate whether the household needs to recharge the account ('currently low') or if the system has low memory ('memory low') and data needs to be downloaded.

decreases in kerosene use: in the baseline the households used 2.5 L of kerosene on average, but this quantity decreased to 1.24 L in the endline.

The households, including both household heads and other adult members, were given detailed instructions on how to interpret the lights. During the first few months of the experiment, the enumerators repeated the instructions multiple times and ensured that the households understand the relationship between the color of the light and the cost of electricity.

5.4. Calculation of the daily self-consumption index

In the pre-analysis plan, this dependent variable was called 'solar fraction.' Here we use the more appropriate term of self-consumption index. Self-consumption ϕ_{SC} is an index for understanding how large share of the power produced on-site is being consumed instantaneously. The value of ϕ_{SC} should be between 0 and 1. The larger the value ϕ_{SC}, the better is the alignment of production and consumption: if $\phi_{SC} = 1$, all produced energy goes directly to use. In this experiment, higher ϕ_{SC} would reduce the need for the battery bank as the reserve and thus the stress for its use. The self-consumption index ϕ_{SC} is formally expressed as

$$\phi_{SC} = \frac{\int_{t1}^{t2} M(t)dt}{\int_{t1}^{t2} P(t)dt}, \tag{2}$$

where $P(t)$ is the generation profile and $M(t)$ is the instantly overlapping part of the generation and load profiles. When $L(t)$ is the instantaneous power consumption (load) and $S(t)$ the power of the storage unit, $M(t) = min\{L(t), P(t) + S(t)\}$. When the storage is being charged, $S(t) < 0$ and when discharged, $S(t) > 0$. In this experiment, the power produced by the PV panels is $P(t) = V_{PV}(t)I_{ch}(t)$, where $V_{PV}(t)$ is the PV panel voltage and $I_{ch}(t)$ is the charging current. The total power demand by the grid (sum including the power consumed by the villagers' loads and any power losses) is $L(t) = V_d I_{load}(t)$, where V_d is the distribution voltage 24 V and $I_{load}(t)$ is the load current from the central charging station to the grid. The power of the battery bank is $S(t) = V_b(t)(I_{ch}(t) - I_{load}(t))$. Values of $V_{PV}(t)$, $V_b(t)$, $I_{load}(t)$ and $I_{ch}(t)$ are measured at the habitation-level central charging stations every 5 min. Self consumption is calculated for each measurement day at the habitation level. The integration limits t_1 and t_2 are chosen daily to cover only the daytime hours when there was PV production. In Table 4 the indices are calculated also for all the measurement day (SC_{24h}), i. e. also when $V_{PV} = 0$. Self consumption is not to be mixed with self-sufficiency index (often called as solar fraction) which is the degree to which the on-site generation is sufficient to fulfil the complete energy need. In this experiment, self-sufficiency index would always approach one since there is only one energy source (solar).

5.5. Data collection

The data was collected between January 2016 and January 2017, over a period of 52 weeks. The data collection was based on technical measurements from the habitation-level and household-level energy meters. These technical devices provided us with the information for the electricity price and consumption over 10-min intervals, along with the necessary voltage and current values from the central charging station over 5-min intervals.

The survey data collection was done by two enumerators from Morsel Research & Development, a Lucknow-based survey company with extensive experience in social science research. Besides 30-min baseline and endline surveys, the enumerators were responsible for weekly surveys of all participating households. They were also responsible for downloading the technical data from the energy meters and central charging stations. The data collection was conducted after the systems had been designed, and the baseline data was not used to inform the design.

The IRB of record is Columbia University, protocol IRB-AAAQ1014.

5.6. Missing data

In general, missing data is not a major problem because (i) the randomization ensures that missingness is not correlated with the treatment assignment and (ii) overall, little data was lost, so that statistical power is not under threat.

In total, 43 households from 7 habitations in the Unnao district participated in the experiment. The expected number of household-weeks was 2236 and the number of habitation-weeks was 364. The weekly surveys had only 4–5 missing household-week observations; technical watt-hour data was lost for 13% of household weeks. At the habitation-week level, 26% of the self-consumption data was lost.

Missingness of technical data can also be assessed at the data point level (10-min interval of recording for households; 5-min interval for habitation-level central charging stations). Here, 14% of data points at the household level were missing and 19% at the habitation level.

One customer in habitation 2 was removed by Boond because he bypassed the meter, so 28 weekly observations of wattage for that household are missing. Due to technical failures of the habitation-level central charging station, there are some missing central charging station observations (3–30%) from different habitations. The central charging station data of habitation 6 is missing for weeks 40–52 and partly corrupt for week 31 due to technical malfunctioning. The central charging station data of habitation 5 is missing for weeks 21–25. In habitation 2, data is missing for weeks 1–8 and 21–24 for an unknown, most probably technical, reason. In habitation 7, the central charging station data was lost for weeks 26–34, possibly due to human error. There is a possibility that some of the data loss issues are results of human error in manual data export and delivery. Throughout the study period, technical problems resulted in intermittent, infrequent data missingness among all households.

5.7. Statistical methods

For most of the analysis, the unit of the analysis is the household-week. In Table 4, it is the habitation-week. We estimate linear regressions with standard errors clustered by the habitation-week (level of treatment assignment and realization). We estimate the linear models with household and week fixed effects. Following the public pre-analysis plan, we need not include any control variables in the main specifications because the treatment is randomized; for models with control variables to enhance precision, see SI Tables S4–S6 (Table 4 is not replicated there because habitation fixed effects subsume all cross-sectional variation).

Author contributions

All authors participated in experimental design and writing of the paper. SY, SN, and JU conducted the fieldwork. SN and SY conducted the data analysis.

Acknowledgements

We thank Boond Engineering & Development for their collaboration on the experiment and Morsel Research & Development for excellent data collection. We also thank Daniel Soto for excellent comments on a previous draft. We acknowledge the support of Fortum Corporation for this research. We thank the Tiina and Antti Herlin Foundation for a doctoral research grant for Sini Numminen. We thank the Finnish Technology and Innovation Agency (TEKES) for funding the microgrid installations through the New Global Project of Aalto University. This work was also partially supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2016S1A3A2925230).

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.esr.2018.05.007. The replication archive is available at http://dx.doi.org/10.7910/DVN/GOPQNZ.

References

[1] Michaël Aklin, Patrick Bayer, S.P. Harish, Johannes Urpelainen, Does basic energy access generate socioeconomic Benefits? A field experiment with off-grid solar power in India, Science Advances 3 (5) (2017) e1602153.
[2] Peter Alstone, Dimitry Gershenson, Daniel M. Kammen, Decentralized energy systems for clean electricity access, Nat. Clim. Change 5 (4) (2015) 305–314.
[3] Frits Møller Andersen, Helge V. Larsen, Lena Kitzing, Poul Erik Morthorst, Who gains from hourly time-of-use retail prices on Electricity? An analysis of consumption profiles for categories of Danish electricity customers, Wiley Interdisciplinary Reviews: Energy Environ. 3 (6) (2014) 582–593.
[4] Severin Borenstein, Stephen Holland, On the efficiency of competitive electricity markets with time-invariant retail prices, Rand J. Econ. 36 (3) (2005) 469–493.
[5] Katherine Casey, Rachel Glennerster, Edward Miguel, Reshaping institutions: evidence on aid impacts using a preanalysis plan, Q. J. Econ. 127 (4) (2012) 1755–1812.
[6] Akanksha Chaurey, Tara Chandra Kandpal, A techno-economic comparison of rural electrification based on solar home systems and PV microgrids, Energy Pol. 38 (6) (2010) 3118–3129.
[7] Anthony L. D'Agostino, Peter D. Lund, Johannes Urpelainen, The business of distributed solar power: a comparative case study of centralized charging stations and solar microgrids, Wiley Interdisciplinary Reviews: Energy Environ. 5 (6) (2016) 640–648.
[8] Ahmad Faruqui, Sanem Sergici, Household response to dynamic pricing of electricity: a survey of 15 experiments, J. Regul. Econ. 38 (2) (2010) 193–225.
[9] Samuel Gyamfi, Susan Krumdieck, Tania Urmee, Residential peak electricity demand response: highlights of some behavioural issues, Renew. Sustain. Energy Rev. 25 (2013) 71–77.
[10] IEA, "World Energy Outlook." Electricity Access Database (OECD/IEA), (2016).
[11] Charles Kirubi, Arne Jacobson, Daniel M. Kammen, Andrew Mills, Community-based electric micro-grids can contribute to rural development: evidence from Kenya, World Dev. 37 (7) (2009) 1208–1221.
[12] Maria Kopsakangas-Savolainen, Rauli Svento, Real-time pricing in the nordic power markets, Energy Econ. 34 (4) (2012) 1131–1142.
[13] Rasmus Luthander, Joakim Widén, Daniel Nilsson, Jenny Palm, "Photovoltaic self-consumption in buildings: a review, Appl. Energy 142 (2015) 80–94.
[14] Johannes Urpelainen, Semee Yoon, Solar products for poor rural communities as a business: lessons from a successful Project in Uttar Pradesh, India, Clean Technol. Environ. Policy 18 (2) (2016) 617–626.