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

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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.

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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).