The Demand for Off-grid Solar Power: Evidence from Rural India's Surprisingly Competitive Retail Power Market*

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Abstract

Over a billion people, nearly all in South Asia and Sub-Saharan Africa, do not have electricity in their homes. Solar technology has advanced and panels have come down sharply in price, making off-grid, distributed solar systems a feasible alternative to grid electrification. What has been the value of this wave of solar innnovation for the poor? This paper reports the results of a randomized-control trial that offered off-grid solar systems at varying prices in one hundred sparsely electrified villages in Bihar, one of India's poorest states. We find that demand for solar is highly price elastic and is near zero at un-subsidized 2013 prices. The high price elasticity appears to be due to a surprisingly competitive retail market where the grid and diesel generator operators compete with off-grid solar. To value solar in this competitive landscape and under counterfactual supply conditions, we estimate a discrete choice demand system for electricity sources using the experimental variation in solar prices. We find that the average household (solar user) is willing to pay USD 2 (USD 6) per year for solar if the grid is absent and USD 0.20 (USD 2) if the grid is present. The willingness to pay for off-grid solar is therefore ten times as large if the grid is not available as a substitute.

I Introduction

In 1879, the year Thomas Edison invented the light bulb, the world's population was around 1.2 billion (The Maddison Project, 2013). Today, a higher number of people, nearly all in South Asia and Sub-Saharan Africa, do not have electricity in their homes. A surge in initiatives by governments and development organizations aims to provide these people with

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access to electricity.[1] These initiatives are predicated on the idea that people value power and thus widening access will benefit households that are currently unelectrified.

The advent of off-grid solar systems has provided a new option for electrification. Former UN Secretary general Ban Ki-moon proclaimed "Developing countries can leapfrog conventional options in favor of cleaner energy solutions, just as they leapfrogged land-line based phone technologies in favor of mobile networks."[2] The traditional mode of electrification, large-scale grid expansion with infill connections of households over time, has very high fixed costs shared over a large population, generating national or even continental economies of scale. Off-grid, decentralized solar also has high fixed costs, but which can be paid even by a single household. The ready nature of solar technology has therefore spurred hope of a faster, greener route to universal electrification.[3] Yet, given off-grid solar systems are sharply limited in their load and still have high costs per unit of energy supplied, it is not clear if off-grid solar electrification can serve as a replacement for the grid, or only a stop gap.

This paper's aim is to answer the question of what are the benefits, specifically willingness to pay, of access to off-grid solar electricity? This question is central to the burgeoning literature on electrification, which is of considerable interest to researchers studying energy access and policymakers considering whether to subsidize solar electricity, grid electricity, or both. The question may seem smaller than the more frequently posed question of the value of electrification, but this broader question is not well posed, because there are a wide variety of suppliers of electricity in many settings, even in poor rural areas. This is because the adoption of off-grid solar electrification is generally not a matter of having or not having electricity, because there are competing off-grid sources of power, like diesel generators, and grid service that vary in terms of load that can be owered, hours of use, and reliability. Thus, the answer to the question of the value of off-grid solar depends critically on the set of competing sources of electricity that are available.

This paper uses a randomized experiment on the pricing and availability of off-grid solar power to estimate a demand system for competing electricity sources. The experiment was conducted in rural Bihar, India from 2013 through 2017 with the implementing partner Husk Power Systems (HPS), a private company that offers solar micro-grids. Each household on

[1] USAID, for example, launched *Power Africa* in 2013 and DFID launched *Energy Africa* in 2015.

[2] As written in "Powering Sustainable Energy for All," *The New York Times*, January 11th, 2012.

[3] See, for example, "Africa Unplugged: Small-scale Solar Power is Surging Ahead", *The Economist*, October 29th, 2016.

the micro-grid gets 25-40 watts of power for 5-7 hours each day. This small quantity of power is used to supply a package, supplied with the system, of a high-efficiency light bulb and an electrical outlet, typically used for mobile phone charging. The experiment has three treatment arms: (i) a pure control arm (34 villages), in which HPS did not offer the system, (ii) a normal price arm (33 villages), where the system was offered at the prevailing price, initially INR 200 a month, later cut to INR 160 per month and (iii) a subsidized price arm at INR 100 a month (33 villages).

We collected a range of survey and administrative data to study the demand and supply of electricity. The primary source of data for the analysis is three rounds of surveys covering roughly three thousand households in the hundred sample villages. Two thick rounds, which we call baseline and endline 1, cover household demographics, income and occupation, time use, electricity access and billing, appliance ownership and use, and health and education measures. A final thin round, endline 2, covers electricity access only. We collected data from three additional sources to characterize energy supply more fully. First, we ran an additional survey to ask diesel generator operators about their cost stricture and customer base. Second, we collected administrative data from HPS on consumer payments. Third, we collected administrative data from the state utilities, which supply all grid power in Bihar, on supply conditions and customer payments.

The first set of results are experimental estimates of the demand for off-grid solar and its benefits for households. We find that demand for micro-grid solar electricity is highly price elastic. At the prevailing (2013) price of INR 200 per month, the demand for HPS solar micro-grids was near zero at the midline and endline, also approximately zero at the endline at INR 160, and about 8% households (both midline and endline) at the below market price of INR 100. These results run counter to the conventional wisdom that there is substantial demand for solar power in remote areas of developing countries, although they fail to provide great insight as to why.

What are the benefits of solar power? Though only a fraction of households adopted solar connections, we find that households in treatment villages are significantly more likely to own light bulbs (i.e., to have any electricity connection), and that they use more electricity, purchase more mobile phones and spend less money charging them. As we would expect, these effects are muted in the normal price treatment arm where adoption was low.

Our surveys also measured welfare outcomes that may be indirectly affected by electricity use in the domains of health and education. For health, electricity may displace kerosene use and therefore reduce indoor air pollution and respiratory infections (Barron and Torero, 2017). We find no significant impact of off-grid solar on self-reported respiratory problems. For education, electric light may increase study time at home and therefore children's test scores. We find no significant impact of off-grid solar on children's reading and math test scores. However, the point estimates for test scores are positive and economically large, the experiment is not well-powered here due to low take-up.

While these impact evaluation results suggest that off-grid solar is valuable to some households, although far from transformative, it is apparent that a structural analysis is necessary to answer the fundamental economic question of willingness to pay for access to solar mini-grids. Further, such an analysis will allow for policy counterfactuals, including about the value of innovation in photovoltaic panels, that the reduced-form experimental analysis is silent on because it misses much of the richness of demand and supply for power in rural India. For example, there is significant heterogeneity across households that governs demand for power. Second, the supply enviornment is surprisingly rich with solar mini-grids in competition with grid electricity, household-specific solar systems, and power provided by diesel generator operatiors. Further, the supply environment was changing rapidly during the experiment: in fewer than four full years, the share of households with electricity from diesel generators fell from 17% to 3%, the share with their own solar systems leapt from 5% to 21%, and the share on the grid skyrocketed from 5% to 41%.

As a solution, we estimate a a nested logit model of electricity source demand in which households' indirect utility depends on electricity source characteristics and household observable characteristics, which have different coefficients for each electricity source. Households can choose not to have electricity, or to adopt one of the grid- or off-grid sources of electricity in their village. Off-grid sources include both the HPS micro-grid, the price and availability of which depends on treatment status, one's own solar panel, and a diesel generator, if a generator operates in your village. The upheaval of the retail electricity market during our sample provides remarkably rich variation in not only price, from the experiment, but also the availability and characteristics of competing technologies, with which to estimate this system.

The nested logit coefficients show that households place a very high value on price. For

example, the effect of increasing the monthly micro-grid price by Rs. 10 (10% of the lowest price in the experiment) on HPS demand is 1 percentage point. Other household demand shifters, such as household size and house characteristics, have precisely estimated coefficients of the expected sign. The mean willingness to pay for the unobserved attributes of the grid is much greater than mean willingness to pay for the unobserved attributes of the three off-grid sources, underscoring these households' preference for access to the grid, even though it is quite unreliable in rural areas. This finding is consistent with media reports that rural households want "real electricity".

The demand system allows us to predict household demand for counterfactual combinations of choice sets and product characteristics. We present counterfactuals on two dimensions, the price of solar off-grid systems and the availability of competing alternatives. In the first counterfactual we reduce the cost for solar photovoltaics and for batteries in line with projections for 2022 and assume these reductions are passed on to consumers, while holding the availability of the alternative sources of electricity constant. This counterfactual could be conceived of as an advance in technology or a subsidy from governments to provide solar electricity.

We find that these projected price decreases would have modest effects. Considering an HPS price cut from INR 200 to a projected INR 70, HPS market share increases by 8 percentage points, and the share of households without electricity declines by 4 percentage points. About half of new customers are therefore coming from non-electrification, while the other half substitute from alternative supply sources. The 10 percent of households that would adopt HPS micro-grids is only slightly above the 8 percent demand at the lowest subsidised price in the experiment.

In a second set of counterfactuals we examine how the effect of solar electricity on electrification and consumer surplus varies with grid availability. The grid increased expanded rapidly in Bihar, so there is substantial variation across our survey waves; we additionally consider extreme scenarios of solar demand under a non-existent grid or an omnipresent grid. We find that the market share of solar and surplus gains due to solar depend critically on presence of the grid as a substitute. For example, if the grid were available in all villages, we estimate that without solar 55% of households would not adopt any electricity source. Introducing solar (both own panels and HPS micro-grids) as options would reduce this number

by 11 percentage points. If instead there were no grid, then the solar effect on electrification would be 29 pp, nearly three times as large.

The consumer valuation for solar likewise depends heavily on the presence of the grid. Absent the grid, the average solar user gains a surplus of roughly USD 6 per year from the availability of solar power (USD 2 averaged over the whole population). This surplus falls to little more than USD 2 if the grid is everywhere (USD 0.20 over the whole population). If the grid is present, many households prefer to adopt the grid and get greater surplus from doing so; the marginal value of solar is therefore ten times lower than if solar were to enter an energy vacuum.

Our paper contributes to the literature on the demand for and effects of electrification. Much of the literature on rural electrification has focused on the spread of grid electricity, and found that grid electrification has large effects on labor supply, productivity and welfare.[4] Relevant to our motivation on the competition between grid- and off-grid sources of power, A recent experiment in Kenya has found that grid electrification is prohibitively costly for many Kenyan households, even at heavily subsidized prices (Lee, Miguel and Wolfram, 2016).

We are aware of two experiments on demand for off-grid solar. Aklin et al. (2017) find that offering off-grid solar power in Uttar Pradesh, India increased electrification rates by 7 pp but had no effect on socio-economic outcomes like expenditures, business creation or time studying. Grimm et al. (2016) find that household willingness-to-pay is high relative to incomes but that nearly no households are willing to pay market prices. These papers are broadly consistent with our findings on welfare. Our analysis takes a step to unify this literature by valuing how solar innovation has benefited households and how this is dependent on household characteristics and competing sources of supply. Our estimates of the valuation of off-grid solar power are complementary to estimates of the benefits of grid power and governments try to set coherent electrification policies that will guide household electrification options and choices.

Our study also contributes methodogically to the development literature by placing a greater emphasis on the external validity of experimental results. Field experiments have

[4] Rud (2012) shows that electrification leads to structural transformation, Dinkelman (2011) demonstrates that electrification can lead to increased employment and female empowerment, Lipscomb, Mobarak and Barham (2013) illustrate how electrification can significantly affect the UN Human Development Index and average housing values, Barron and Torero (2017) find that household electrification reduces indoor air pollution.

lately gotten longer to address the realism and durability of effects.[5] The analysis of experiments more often incorporates structural modeling to understand how an intervention works and to extrapolate from reduced-form treatment effects to relevant policy counterfactuals (Duflo, Hanna and Rya, 2012; Bryan, Chowdhury and Mobarak, 2014). Our experiment offered long-term subsidies on solar technology, on a standing basis for everyone in treatment villages, and tracked take-up and welfare outcomes over three-and-a-half years. The experimental variation therefore closely mimics real-world variation in the price of a technology. We use this variation to recover the price elasticity of demand for electricity sources in the context of a discrete choice model which encompasses several alternative sources of power. Thus the experimental results are embedded in the larger context and our experimental estimates would enable us to address counterfactuals, such as the value of grid expansion, that lie well beyond the boundaries of the experiment itself.

The rest of the paper is organized as follows: Section II describes the experimental design and the data, Section III presents the reduced form results from the randomized control trial, Section IV details our model of demand for electricity connections, Section V presents the demand estimates and counterfactuals and Section VI concludes.

II Experimental Design, Data and Context

This section describes the setting for the study, the experimental design and the data collection. We then use the data to characterize the electricity sources competing within our study sample.

We conducted our experiment in Bihar, one of the poorest and most energy deprived states in India. Table 1 compares the percapita GDP, access to electricity, and annual per-capita electricity consumption of the United States, India, Sub-Saharan Africa, and Bihar. Bihar's per capita GDP is a quarter of that for India as a whole and its electricity consumption per capita only 15% of the Indian average. The mean Bihari electricity consumption of 122 kWh per capita per year is a quarter of that in Sub-Saharan Africa. At this average level of consumption, each person can power two light bulbs totaling 60 watts for six hours per day through the year.

[5] De Mel, McKenzie and Woodruff (2013) study firm formalization with a 31-month followup, Dupas and Robinsona (2013) study household savings with a nearly 3-year follow-up and

II.A. Experimental Design

We partnered with Husk Power Systems (HPS) to vary the availability and price of solar micro-grids in a randomized-control trial. Husk Power was founded in 2007 to provide electricity in rural areas using biomass gasifiers as generators to generate power from agricultural waste, such as rice husks (hence the name of the company). These biomass plants could only serve a village if demand was sufficiently great (e.g., 100 households) and were subject to fuel supply disruptions. HPS made a strategic decision to add a solar micro-grid product to its portfolio for flexibility in reaching a wider set of villages.

The HPS solar product is a solar micro-grid. The micro-grid consists of a 240 watt panel is shared among 6 to 9 households. Each households gets its own 3.2 volt rechargeable battery and its own meter. Meters have key pads to unlock access to the battery and therefore the system and households must purchase codes each month to keep the system unlocked. Each household on the micro-grid gets 25 to 40 watts of power for 5 to 7 hours each day. This quantity of power is very small and is used to supply a package, supplied with the system, of a high-efficiency light bulb and an electrical outlet, typically used for mobile phone charging.

Our experiment sample consisted of 100 villages distributed across three districts in Bihar, as shown in Figures 1a and 1b. These villages were chosen to fulfill three criteria. First, they were not listed as electrified villages by the government. This implied that either grid connections were entirely unavailable, or very few households were connected to the grid. Second, villages were chosen to be reasonably close to existing HPS operating sites, so that micro-grid services could be feasibly expanded to these areas. Third, sample villages had not already been offered HPS micro-grids. The total population of households in all 100 villages was 48,979.

The experiment is a cluster-randomized control trial at the village level. The experiment had three treatment arms that vary the availability and price of an HPS system: a control arm (34 villages), in which HPS did not offer micro-grids, a normal price arm (33 villages), in which HPS offered micro-grids at the prevailing price of INR 200 per month, and a subsidized price arm (33 villages), in which HPS offered micro-grids at the reduced price of INR 100 per month. While the prevailing price at the start of the experiment was INR 200, HPS later cut this price—within this experimental arm only—down to INR 160, due to a lack of demand at the higher price. Therefore the normal price arm consists of an initial price of INR 200 and

a later price of INR 160.

The offers of these connections and prices were available to all households within a village, regardless of whether they had previously expressed interest in HPS's product or whether they were surveyed as part of our experimental data collection. Sales of solar micro-grid connections began in January 2014.

II.B. Data and Covariate Balance

Our primary source of data is a household panel survey with three waves. We also collected administrative data on payments by customers to HPS, survey data on supply costs for diesel generator operators, and administrative data on power supply and customer payments from the electricity distribution company.

The household survey sample was drawn to represent households who stated an interest in a solar connection. In August 2013, a customer identification survey was conducted in all sample villages, to elicit the stated willingness of households to pay for a solar micro-grid connection. A random sample of 30 households per village was drawn from those who reported they would be interested in paying for a solar connection at a price of Rs. 100 per month. In practice, this identification of potential customers was barely restrictive. Households were not required to put down a deposit and were not held to their statement of interest when the product was eventually offered. Over 90 percent of households with no electricity or diesel-based electricity said they would be interested in using micro-grids. These households alone accounted for over **[insert number]** percent of the population. Over 70 percent of households with a grid electricity connection or home solar panels, expressed an interest in the solar connections.[6] We therefore expect that our survey sample represents all or nearly all the potential solar users in the population.

The household survey panel consists of two thick rounds that we call baseline and endline 1 and one thin round that we call endline 2. The baseline household survey was conducted in November and December 2013 and covered demographics, income, assets and appliance ownership, electrification status and select measures of education and health. The survey covered all energy sources used by households, payments associated with these sources, and other characteristics such as capacity or hours of supply. The endline 1 survey was conducted

[6] As Section **??** makes clear, the share of households who expressed an interest in using solar micro-grids was vastly higher than actual take-up rates.

in May through July, 2016 and used nearly the same survey instrument. The endline 2 survey was conducted mainly as a check-up on demand for solar a year after the first endline. This wave did not include characteristics of other sources or detailed household covariates of the first two waves.

We collected administrative data from HPS on monthly payments from customers from January 2014 through April 2016, which we match with our household survey data to estimate demand for HPS solar over time between our survey waves.

We surveyed diesel generator operators to get monthly information on cost structure, hours of operation, connection plans, and number of customers, over a two-year period from January 2014 to 2016.

We also construct a time-series of electricity consumption and payments of households connected to the electricity grid. We collect grid consumer IDs in our third household survey, as use these to find sample households in administrative data. The time series includes monthly units billed, which is based on units consumed for metered households, and average units consumed for unmetered households. We observe the value of each bill and payment.

Table 2 shows the balance of covariates in our baseline survey across treatment arms for demographic variables (Panel A), wealth or demand proxy variables (Panel B) and energy access (Panel C). The first three columns show the mean values of each variable in the control, normal price and subsidized price arms, with standard deviations in brackets. The next two columns show the differnces between the normal price and control arms and subsidized price and control arms, respectively, with the standard error of the difference. The final column shows the F-stat and p-value from a test of the null that the treatment dummies are jointly zero at baseline.

The joint test rejects the null of equality of treatment arms at the ten percent level for three out of twelve variables at baseline, somewhat higher than would be expected by chance. For example, households in subsidy villages are more likely to have solid or pukka houses than control households and to have solid roofs (these variables are likely to be highly correlated). The overall rate of electrification does not differ by treatment arms (p-value 0.54, variable "Any elec source (=1)", but households in the subsidy treatment arm are more likely to have electricity from the grid and somewhat less likely to have it from a diesel generator. We address this slight imbalance by including baseline household covariates as controls in both

our reduced-form and structural estimates.

Considering the control group, the baseline covariates describe a population poorer and more rural than Bihar as a whole, as would be expected given our sample selection criteria. Self-reported household incomes averaged INR 7,460 per month (USD PPP 2.6 per person per day).[7] Two-thirds of households own agricultural land and about a quarter have a *pukka* house, constructed of solid materials like brick. The average household has 3.3 adults living in 2.4 rooms. A quarter of households have electricity from any source, with the most common source at baseline being diesel electricity.

II.C. Electricity Source Characteristics

The solar micro-grid offered by HPS did not enter a vacuum but a marketplace in which diverse sources of electricity were competing. Table 3 describes these alternative choices, which we discuss in detail below. Each panel of the survey represents the source characteristics as of each of our survey waves.

II.C.1. Grid electricity

In addition to solar micro-grids, formal electricity connections to the distribution grid were also available in some villages in our sample. The availability of grid connections in a village depends on how close the village is to the grid. If the grid reaches a village, households connect in two ways. The formal way is to file an application with the state distribution company during government 'connection camps', or through a linesman, licensed revenue collector, or power contractor. The informal way is to hire a local electrician to wire a connection, possibly paying bribes to utility staff to look the other way.

In order to categorize households as having formal or informal connections, we collected household consumer IDs from grid customers during the follow-up survey conducted after the endline. We matched these IDs with consumer IDs in three grid administrative data sets: a consumer base dataset of all formal customers, a billing dataset containing monthly billing prices and quantities, and a collection dataset of receipts for payments from customers to the distribution company.

[7] Self-reported income can often be very imprecise in rural households with earnings from a combination of livestock, agriculture, and intermittent or seasonal wage labor. For this reason, self-reported expenditure is frequently preferred to income as a measure of household cash flow. In our sample, households report average monthly expenditures of INR 10,733.

We define households as formal if they were successfully found in the consumer base data. For all such formal consumers, we can observe the bills they received as well as the payments made. Informal consumers include households whose consumer IDs could not be found in the administrative datasets, or were not provided to us at all. Some consumers also received electricity bills but had made no payments over the last 12 months and we categorize these as informal connections as well.

Table 3, column 1 describes some characteristics of grid electricity from our survey data. Grid users pay the highest price of any electricity source at baseline, of INR 153 per month (Panel A). For this price they are able to connect the highest average load amongst users of any source. The grid is only available in 35% of villages, however, and when the grid is available the supply is not continuous but for an average of 7.4 hours per day.

II.C.2. Diesel

At baseline diesel generators were a popular source of off-grid electricity. Diesel was supplied by village residents who had purchased a generator and offered connection plans with monthly or semi-monthly payments.

Table 3, Panel A, column 2 summarizes the characteristics of diesel connections at baseline. Diesel generators are cheaper than the grid, at INR 100 per month on average, but support lower average loads of 147 watts. While there was some variation in the plans offered, the modal option consisted of a 100 watt connection for INR 100 per month through which customers could power one or more light bulbs, or charge mobile phones in the evening.[8] Generators run on a predictable schedule in the evening and early night-time for an average daily supply of 3.4 hours. Because diesel operators require a sufficient number of customers to support their fixed costs, diesel was available in only 39% of villages at baseline.

II.C.3. Own solar

Households can buy and operate solar systems on their own, which we refer to as "Own Solar" to distinguish it from the HPS micro-grid system. Households paid for these panels upfront and would usually have to travel to a larger market town or city to make a purchase.

[8]The solar micro-grid provided similar lighting services at a much lower wattage because of the provision of highly energy efficient LED lights with the connection.

Because these markets were in principle accessible to all villages in our sample, we assume that households in any village could have bought such a system if they wished.

Table 3, Panel A, column 3 summarizes the characteristics of own solar connections at baseline. We translate the capital costs of own solar into an equivalent monthly payment using an assumed lifetime of 7 years and interest rate of 20%. The characteristics of Own solar are strikingly similar to diesel at baseline, with similar monthly prices and supported loads. Own solar users report they can use their systems for 7 hours per day, significantly longer than users of diesel systems.

II.D. Electricity Source Market Shares

Over the course of the study from 2013 to 2017 there was a complete upheaval of the retail electricity market in rural Bihar. The government dramatically expanded the grid and solar got cheaper and better, so that these two sources of electricity overtook diesel generators.

In Figure 2, we plot the share of households using different electricity sources during the baseline, endline 1 and endline 2 surveys. Each group of bars represents the households with electricity from a given source, and each bar within a group the share of households with that source in each of the three survey waves. The experiment is represented by the first group of bars: HPS micro-grids were basically non-existent at baseline, increased to an 11% share of all households at endline 1 (averaged across treatment arms), and then fell back.

The experiment occurred amidst a broader upheaval of the market. The share of households with own solar systems rose from 5% to 6% and then 21% over three survey waves. Referring back to Table 3, Panels A through C, in column 3, we can see that own solar systems got much cheaper over the study period: the average system cost INR 100 per month at baseline and just INR 50 per month by the endline 2. The diesel share fell from 17%, the highest in the baseline, to 3%, amidst increased competition, as many diesel operators exited the market. The number of grid connected households skyrocketed from 5% at baseline to 25% at endline 1 and 41% at endline 2. The government launched a concerted campaign to electrify villages and to connect households in those villages through connection camps. Since our sample villages were chosen for being initially un-electrified, our data collection bears witness to a massive increase in grid connections from this campaign.

The market upheaval therefore appears to have involved several factors at once: falls in

solar price, a dramatic expansion of the grid by the government, and the endogenous exit of diesel generators from the market. The following Section III reports on the demand for solar micro-grids and their impacts in isolation. The Section V, afterwards, widens the scope of analysis to include the entire demand system of competing electricity sources. With this demand system we can then break down how much each change in the market has benefited households.

III Reduced-form Results

III.A. Demand for HPS Solar

Our experiment allows us to estimate the demand curve for solar micro-grid connections.

As we describe in Section II, households made monthly decisions on whether to pay for electricity from Husk Power Systems. Households that did not pay would eventually be disconnected but from month to month this risk was very low.[9] Consequently the demand for micro-grids, defined by the household decision to pay for this service, changes every month.

Recall that the micro-grid option was made available to households living in villages assigned to the normal price and subsidized price treatment groups at INR 200 and INR 100 respectively. Twelve months into the experiment, micro-grid connections were made available to households in the regular price group at INR 160 per month. The random assignment of prices to villages allows us to trace out the demand curve for solar micro-grid electricity.

In Figure 3, we plot the share of households choosing to pay for micro-grid electricity at different prices and over different time intervals. Each separate line on the figure refers to payment at a different horizon: at least once during the experiment, midway through during months 16-18, and at the time of the endline 1 survey at month 29. Three features of consumer demand stand out. First, the demand for micro-grid electricity at the normal price prevailing before the experiment is practically zero: only about two percent of households paid even a single month in this arm. Second, demand is highly elastic, and increases to a total of about 17% of households that paid once during the experiment. Third, demand shifted in over the course of the experiment, such that even at the subsidized price only 7% of households were

[9] This is an accurate description of how the contract between the micro-grid supplier and consumers played out *in practice*. On paper, Husk Power Systems had an internal rule mandating that households who did not pay for three consecutive months be disconnected, but this was sporadically enforced.

paying by the time of the endline 1 survey.

Figure 4 shows the costs of supply for HPS per system per household. The total monthly cost, in the left bar, is nearly USD 2 (INR 120) per month just for the system installation cost, excluding all variables costs of billing, collection and system maintenance.[10] Therefore the estimated demand curve implies that demand is near zero at unsubsidized 2013 prices. The price sensitivity we find for solar micro-grids agrees with other work that finds household demand is nearly zero when off-grid solar is priced at cost (Aklin et al., 2017; Grimm et al., 2016).

III.B. Impacts of Access to Off-grid Solar

The demand curve reflects household willingness-to-pay for off-grid solar. This sillingness-to-pay reflects perceived household benefits to having a connection. There may also be benefits of solar power that are not perceived by the household or not valued by the household decision-maker in buying a connection. For example, improved lighting could lead to children having more time to study at home, which may or may not be valued by parents. There may also be intra-household spillovers from reduced kerosene consumption and indoor air pollution (Barron and Torero, 2017).

We estimate the impact of access to electricity on a battery of social outcomes. We begin by estimating a reduced form model of the following type

$$y_{ivt} = \alpha + \beta_N NormalPrice_v + \beta_S SubsidizedPrice_v + \delta X_i.$$

Here y_{ivt} is the outcome of interest for household i in village v at time t. $NormalPrice_v$ and $SubsidizedPrice_v$ are dummies that take the value 1 when village v was assigned to solar micro-grids at regular and subsidized prices respectively. X_i is a vector of controls from the baseline survey. The outcomes y may include measures of electricity access, adult and child respiratory problems, reading and math test scores, and household income.

Households in the treatments got and used electricity micro-grids. The micro-grid powered two low wattage LED lamps and one mobile charging point provided with every connection. Table 4 reports regressions of ownership of these appliances and use of electricity on treatment

[10] Capital costs as reported by our partner HPS are additionally net of capital subsidies provided by the government, which were of the order of 60% in 2014.

status. The intent-to-treat effect of assignment to a subsidy treatment village is to increase light-bulb ownership by 15 percentage points (standard error 4.7 pp) on a base of 32 percentage points in the control (column 1). Subsidy treatment households increased hours of electricity use by an estimated 0.94 hours per day (standard error 0.24 hours per day) relative to 1.16 hours in the control (column 2). The effects of being assigned to a normal price village are smaller but still statistically significant. Households assigned to a subsidy treatment village are also more likely to own a mobile phone, by 3.4 pp on a high control ownership rate of 88 percent (column 3) (implying that control households are 2.75 times as likely to own a mobile phone as a light bulb). Finally, assignment to a subsidy treatment village also decreases the amount spent charging one's mobile phone. This effect is because households without electricity will typically charge their mobile phones at a shop for a small fee, such as Rs. 5, which nonetheless implies a high unit cost of energy.

Therefore, the intervention had a meaningful first stage. We find that when solar micro-grids are made available, households use more electricity, purchase more mobile phones, and spend less money charging them. As we would expect, these effects are more pronounced when the monthly costs of solar electricity connections are low.

Table 5 now turns to consider the effects of off-grid solar on social and economic outcomes, for health, education and test scores. Panel A of the table is the reduced-form or intent-to-treat effect for these outcomes, and Panel B is the instrumental variable estimate of the coefficient on hours of electricity using the two treatment assignment dummies as instruments.

We find no evidence that respiratory problems decrease for adults or children (Panel B, columns 1 and 2). The predominant source of indoor air-pollution comes from cooking, which is unaffected by the provision of micro-grids, and we do not find significant declines in kerosene expenditure (not reported). Effects on reading test scores are positive but imprecisely estimated (columns 3 and 4). For example, we estimate that an hour of additional electricity use increase children's reading scores by 0.22 standard deviations (standard error 0.22 standard deviations). This is a fairly large standardized effect but imprecise due to low first-stage take-up and the children tested being only a subsample of the overall experiment. We cannot rule out a zero effect or a significant positive effect of lighting on child test scores. Finally we find that electricity has a null effect on household income of INR 150 per month (standard error 350), which is small compared to baseline income of INR 7,500 per month.

Overall we find little evidence that the electricity provided by solar micro-grids had large welfare impacts, with the caveat that our estimates for education outcomes are imprecise. Households still value off-grid solar for lighting and other energy services. Of course, households may also see greater benefits from other types or sources of electricity, in particular sources that support higher loads. The next section introduces a model to understand how households value off-grid solar relative to alternative sources of electricity.

IV Model of demand for electricity connections

We estimate a nested logit demand model over electricity sources using household-level survey data. The experiment varies the price of solar power across villages to help identify the coefficient on price. The price of $OwnSolar$ has also declined over time.

In future revisions, we intend to use a mixed logit model estimated with our survey micro data (Berry, Levinsohn and Pakes, 2004). The mixed logit model will introduce unobserved consumer heterogeneity and allow us to explicitly instrument for the price elasticity, therefore using only the experimental variation to estimate this coefficient.

IV.A. Model specification

Households i live in villages $v = 1, \ldots, V = 100$ at times $t = 1, 2, T = 3$, which correspond to survey waves. Each household chooses an electricity source $j \in \{ None, Diesel, Grid, OwnSolar, HPSSolar \}$. Each electricity source j has observable characteristics x_{jk} with $k \in \{Price, Load, HoursUse\}$.

Household indirect utility from electricity connections is given by

$$\begin{aligned} U_{vtij} &= V_{vtij} + \epsilon_{vtij} \\ &= \delta_j + \mathbf{x}_j' \beta^1 + \mathbf{z}_{vti}' \beta_j^2 + \epsilon_{ijt}. \end{aligned}$$

The utility specification allows coefficients β^1 on source characteristics $\mathbf{x}_j$ and source-specific coefficients β_j^2 on household characteristics $\mathbf{z}_{vti}$. Household characteristics are as described in Table 2, Panels A and B, and consist of demographics, income, wealth proxies and demand shifters (like number of rooms). The table describes the characteristics at baseline but the model uses household characteristics by survey wave, hence the time index. The parameter

δ_j gives the mean indirect utility for each technology. The consumer chooses j that provides the highest indirect utility. We normalize the mean indirect utility of the outside option, no electricity, to zero.

The nested logit specification is that the vector of shocks ϵ_i across alternatives j is jointly distributed with cumulative distribution function

$$\exp\left(-\sum_{k=1}^{K}\left(\sum_{j\in B_k} e^{-\epsilon_{ij}/\lambda_k}\right)^{\lambda_k}\right).$$

The index $k \in \{None, Grid, OffGrid\}$ indicates the nest, giving the type of electricity source. Let B_k be the set of sources in nest k. The parameter λ_k is related to the correlation of unobserved choice shocks within a nest by $\lambda_k = 1 - \rho_k$. We estimate the parameters of the above indirect utility function via maximum likelihood.

IV.B. Calculation of willingness-to-pay for solar power

Given the coefficients in the model, we calculate the consumer surplus loss from removing an alternative from the choice set. For a fixed set of options J in nests k the steps are

1. For a given consumer i, calculate the observable component of indirect utility $\widehat{V}_{vtij}$ for every choice j using $\hat{\delta}_j, \hat{\beta}^1$ and $\hat{\beta}^2$.

2. Calculate the inclusive value of each nest k as

$$IV_{ik} = \ln \sum_{j\in B_k} \exp(\widehat{V}_{vtij}/\lambda_k).$$

3. Calculate the choice probability for nest k as

$$P_{i,B_k} = \frac{\exp(\lambda_k IV_{ik})}{\sum_k \exp(\lambda_k IV_{ik})}.$$

4. Calculate the expected consumer surplus from the set of options available as

$$\mathbb{E}[CS_i|J] = \sum_k P_{i,B_k} IV_{ik}.$$

We can calculate the above for the given choice set and an alternative choice set J'. We then calculate total expected willingness-to-pay for the expanded choice set as

$$\sum_i - \left(\mathbb{E}[CS_i|J'] - \mathbb{E}[CS_i|J]\right) / \beta^1_{i,price}.$$

The expression in parentheses is the difference in expected consumer surplus under the two choice sets, which may include different availability of power sources or different characteristics for those options. We translate the difference in consumer surplus into willingness-to-pay, in monetary terms, by dividing by the coefficient on price, and sum over consumers.

V Demand Estimates and Counterfactuals

This section reports estimates of the demand system. We then proceed to use these estimates to run counterfactual simulations predicting electrification and consumer surplus under different prices, qualities and availability for solar power and for other sources of electricity.

V.A. Demand estimates

Table 6 presents estimates of the parameters of the nested logit demand system. The coefficients in the first panel give the effects of source characteristics for price and hours on the mean indirect utility of a choice. The coefficients in the second panel give source-specific effects of household covariates on mean indirect utility for each electricity source.

We estimate a negative and precise coefficient of -1.053 (standard error 0.099) on price (column 1). Household observable characteristics are powerful determinants of demand. For example, considering the demand for grid electricity in column 1, then *Monthly income* as well as *Solid roof (=1)*, *Number of rooms*, *Pukka (solid house) (=1)* and *Agricultural land (=1)* all have statistically significant and economically meaningful effects on demand. These characteristics can be considered as direct demand shifters, for example one might need more light in a house with more rooms, but also as proxies for household wealth not captured by monthly income. Demand is increasing in the demographic variables of the *Number of adults* in a household and *Literacy of household head*.

The coefficients on household characteristics in demand for HPS Solar and Own Solar are similar to those for grid electricity, with some small departures. HPS Solar and Own Solar

point estimates for the effect of income on demand are higher than for Grid electricity, though these differences are not statistically significant. Owning agricultural land has a coefficient of 0.527 (0.121) for HPS demand and 0.409 (0.089) for Own Solar demand, versus 0.177 (0.071) for Grid demand. This may reflect that demand for off-grid sources is higher in more agricultural and therefore less densely settled areas (though our entire sample is rural).

The model fits actual market shares for different technologies well. Table 7, Panel A shows the actual market shares as of the time of our endline survey and the predicted market shares in the model. The actual and predicted market shares are generally within one percentage point.

V.B. Counterfactual simulations

Our demand system allows us to predict household demand for counterfactual combinations of choice sets and product characteristics. We consider several changes of special interest that vary the prices, availability and quality of different electricity sources.

V.B.1. Counterfactual scenarios

First, and most directly related to the experiment, what would be the effect of further reducing solar prices on HPS solar market shares? We obtained administrative estimates from our partner HPS on the cost of their system. Figure 4 shows the installation cost of the system in units of amortized USD per month, in the first column, broken out by the cost for each component of the system. The total cost is about INR 114 (USD 1.90) per month, which is above our lowest subsidized price of INR 100 per month. At the normal price of INR 160, and without allowing for any variable costs of labor and collections, which are certainly not negligible, this cost basis would imply a profit margin of 40%. The capital component of the cost is USD 0.70 per month or about 37% of the total cost.

In the first counterfactual we consider reductions in cost for solar photovoltaics and for batteries. For solar PV, we assume a 55% reduction in cost in line with the National Renewable Energy Laboratory's projections for 2022 (Feldman, Margolis and Denholm, 2016). For batteries, we assume that they fall in cost by 75% in accord with the US Department of Energy's 2022 goal (Howell et al., 2016). Since panel capital and batteries only make up part of a system, these changes imply a reduction in price to about INR 70 overall, or 30% cheaper

than our subsidy treatment.

Second, the experimental estimates apply to an environment where grid supply is only available for some households. The effects of solar on electrification rates would have been different if the grid was everywhere, so households had better substitutes, or if the grid has non-existent, as is the case in some parts of India and much of rural Sub-Saharan Africa. We predict demand under these scenarios by adding or removing grid electricity from the choice set.

Third and finally, the estimates allow us to back out improvements in solar quality over time. In ongoing work we intend to use these changes in unobserved "quality" to infer the potential solar demand if the marketing and distribution of solar systems improved.

V.B.2. Counterfactual results

Figure 5 presents market shares of different electricity sources under changes in HPS prices. The prices, on the horizontal axis, range from INR 70 per month in the reduced cost scenario up through the range of our experimental treatments to INR 300 per month; Table 7, Panel B reports market shares at specific prices along this curve. The vertical axis shows market shares as indicated by the curves for each technology.

The figure shows that further cuts in price would increase the HPS market share moderately. At the lowest subsidised price from the experiment, 11 percent of households adopt in the model. Setting the price of the system at the 2022 projected cost, adoption increases to 14 percent. Looking across the other electricity sources, it is clear that most of this gain in market share comes from households that would not otherwise be electrified (dashed line at top). For example, considering an HPS price cut from INR 200 to INR 70, HPS market share increase by 10 pp, and the share of households without electricity declines by 6 pp. Thus over half the new customers are coming not from other sources of power but from non-electrification.

Table 7, Panels B through E show the effects of removing solar as a technology from the choice set under differing grid conditions: the absence of the grid (Panel B), partial grid observed in Bihar at baseline for 29% of villages (Panel C), partial grid observed at endline for 54% of villages (Panel D), and complete grid availability (Panel E). In each panel HPS solar is assumed to cost INR 100. The effect of solar technology on electrification rates depends greatly

on whether the grid is available as a substitute. In Panel E, with the grid everywhere, solar captures an 0.16 market share if available and reduces the share of non-electrified households by 0.06. In Panel B, when we have removed the grid from the choice set, solar captures a 0.3 market share and reduces the share of non-electrified households by 0.32. Thus the effect of solar on the share of households without electricity is more than three times as large when alternatives such as grid electricity are not available.

Figure 6a puts these changes in market shares in terms of household willingness-to-pay for solar. We calculate the consumer surplus from the bundle of offered electricity sources in our model, recalculate this surplus without solar power in the choice set, and then normalize the difference in surplus by the estimated household price coefficient to get household-specific willingness-to-pay. The figure reports the value of household WTP averaged over all households (blue bars) and over households that adopt solar (red bars). The four sets of bars show WTP for both groups of consumers depending on the availability of the grid.

The second set of bars from the left shows that under the conditions at our baseline survey, in 2013, of limited grid availability but with diesel generators present in many villages, households using solar would gain a surplus benefit of USD 5 per year on average from the availability of solar power (assumed to have 2017 characteristics). Averaged over the whole population, this is somewhat more than USD 1 per household. If the grid were more widely available, as at our endline, these figures would drop considerably. If the grid were present in every village, household WTP for solar would fall to less than than USD 2 for solar users and barely USD 0.20 over the whole population. The presence of competing sources of electricity, particularly grid electricity, reduces the valuation for innovation in solar power sharply.

VI Conclusion

[TO COME]

VII Figures

Figure 1a: Map of sample districts in India

Figure 1b: Map of sample villages in Bihar

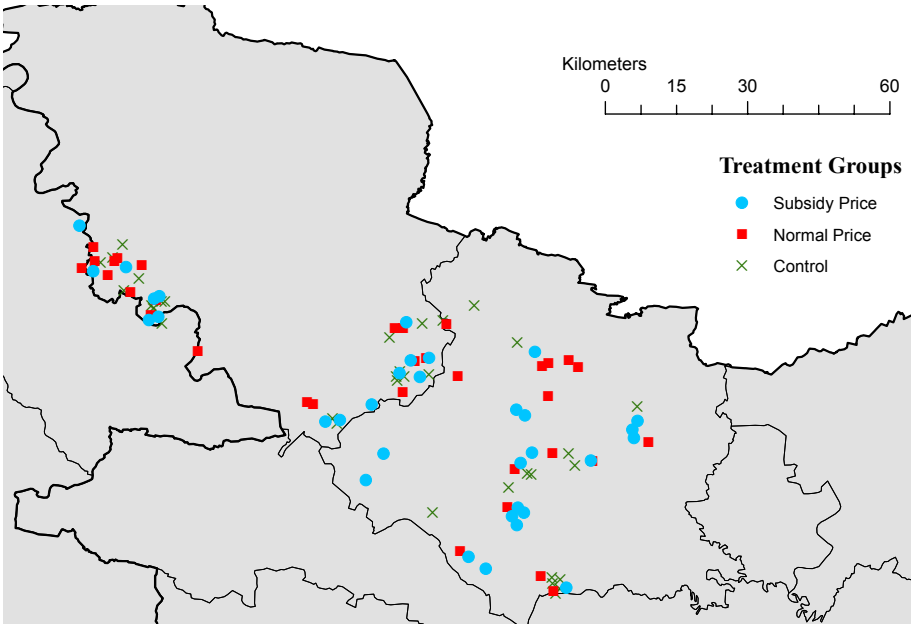


Figure 2: Take-up of electricity sources across household surveys

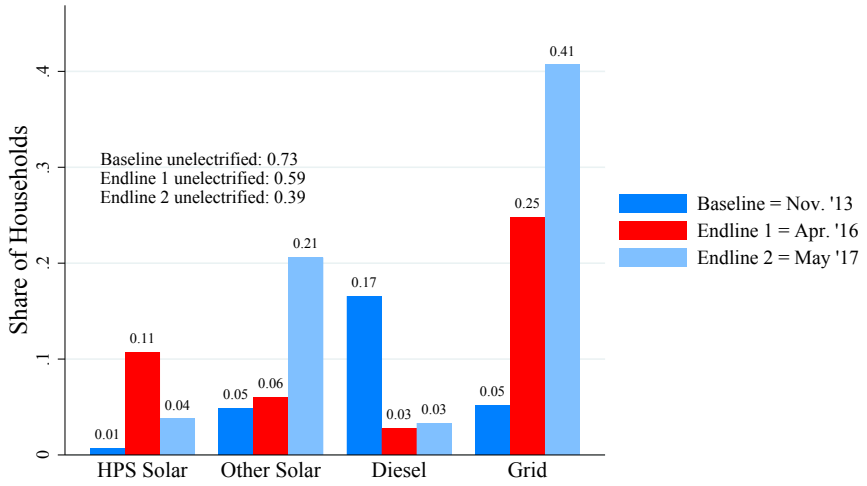
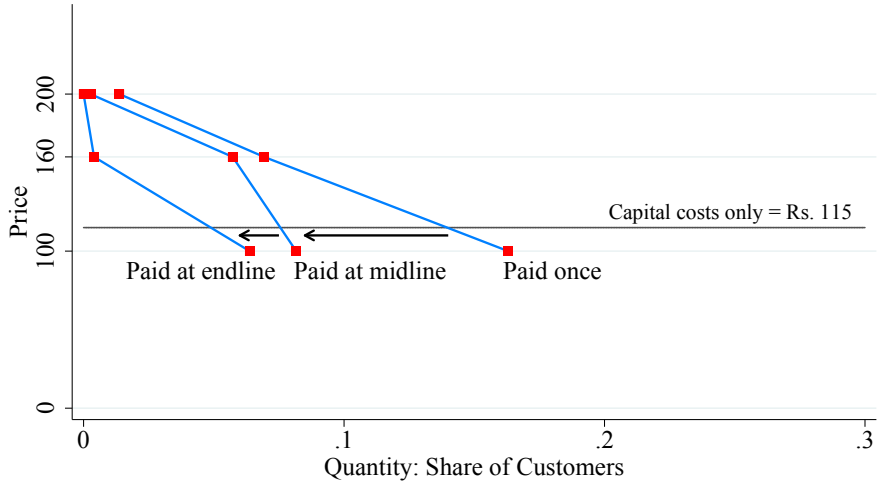


Figure 3: Demand curve for HPS solar



"Paid at midline" includes households that paid during April, May, and June 2015, which correspond to the 16th, 17th, and 18th months of the experiment. "Paid at endline" includes households that paid during the final three months preceeding endline 1 (months 26, 27, and 28).

Figure 4: HPS price under current and counterfactual capital costs

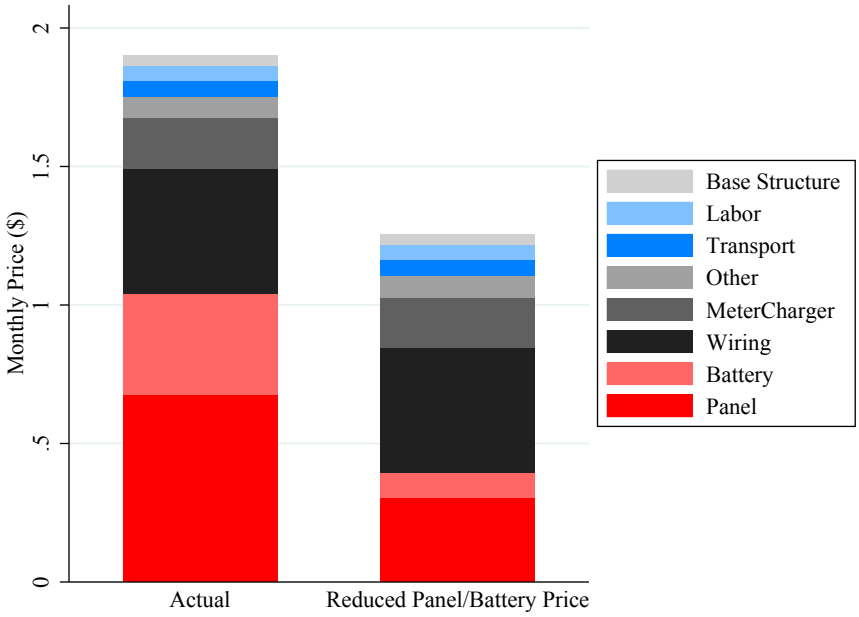
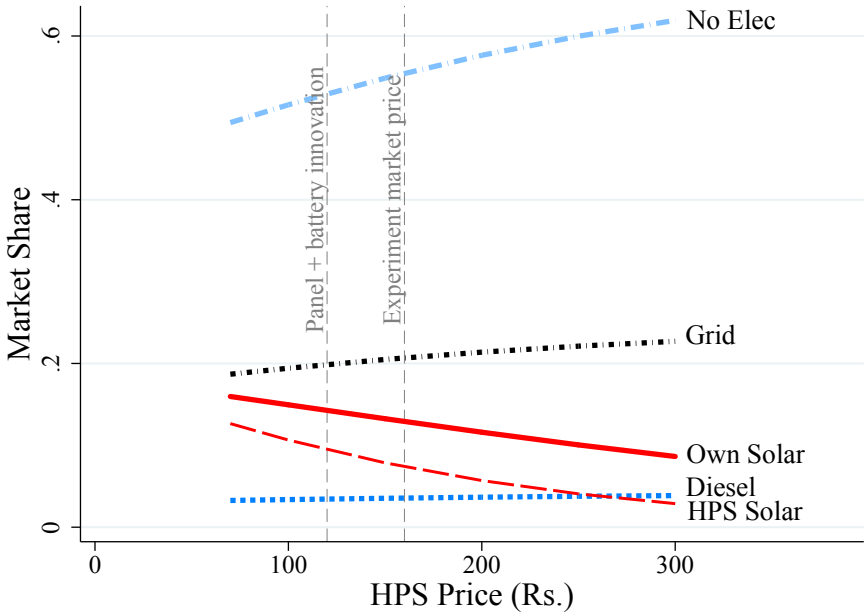
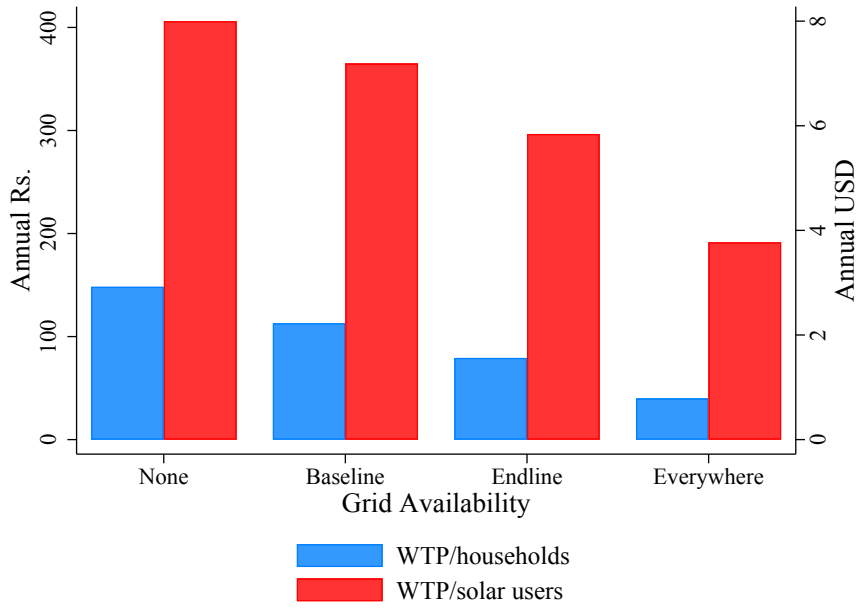


Figure 5: Market shares under varying HPS prices



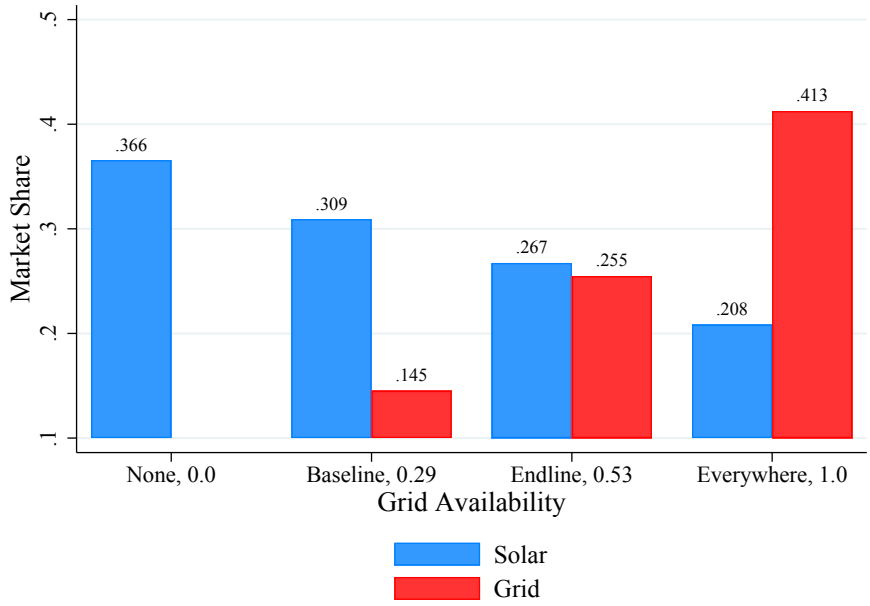
Counterfactual assumes endline 1 covariates.

Figure 6a: WTP for solar under varying grid availability



Counterfactuals are applied to endline 2 covariates to reflect the change in own solar characteristics observed in our third panel. HPS price is assumed to be Rs. 100 per month.

Figure 6b: Market shares under varying grid availability



VIII Tables

Table 1: Electrification context

Location	US	India	Sub-Saharan Africa	Bihar
GDP per capita (USD)	57,467	1,709	1,449	420
kWh per capita	12,985	765	481	122
Electricity access (% of population)	100	79	37	25
kWh per capita / US kWh per capita	1	0.059	0.037	0.009

Source: World Bank (2015, 2017)

Table 2: Baseline covariate balance

	Control	Normal	Subsidy	Diff(N-C)	Diff(S-C)	FTest
	Panel A. Demographics					
Literacy of household head (1-8)	2.44	2.69	2.60	0.25	0.16	1.33
	[2.04]	[2.15]	[2.10]	(0.16)	(0.15)	(0.27)
	1031	971	989	2002	2020	
Number of adults	3.31	3.50	3.49	0.20*	0.18*	2.19
	[1.58]	[1.75]	[1.78]	(0.11)	(0.11)	(0.12)
	1052	983	1001	2035	2053	
	Panel B. Wealth Proxies					
Income (Rs. '000s/month)	7.46	7.32	7.28	-0.14	-0.18	0.068
	[6.91]	[6.93]	[7.09]	(0.57)	(0.51)	(0.93)
	1041	963	983	2004	2024	
Number of rooms	2.40	2.55	2.53	0.15	0.13	1.29
	[1.32]	[1.45]	[1.45]	(0.10)	(0.098)	(0.28)
	1052	981	999	2033	2051	
House type (pukka = 1)	0.24	0.27	0.31	0.035	0.074**	2.79*
	[0.43]	[0.45]	[0.46]	(0.037)	(0.031)	(0.066)
	1052	983	1001	2035	2053	
Owns agricultural land	0.67	0.69	0.67	0.015	0.0022	0.045
	[0.47]	[0.46]	[0.47]	(0.056)	(0.053)	(0.96)
	1052	983	1001	2035	2053	
Solid Roof (=1)	0.42	0.46	0.51	0.042	0.095**	3.08*
	[0.49]	[0.50]	[0.50]	(0.043)	(0.039)	(0.050)
	1052	983	1001	2035	2053	
	Panel C. Energy Access					
Any elec source (=1)	0.25	0.31	0.27	0.061	0.022	0.63
	[0.43]	[0.46]	[0.44]	(0.055)	(0.050)	(0.54)
	1052	983	1001	2035	2053	
Uses gov. elec (=1)	0.030	0.036	0.091	0.0052	0.060**	2.53*
	[0.17]	[0.19]	[0.29]	(0.017)	(0.028)	(0.085)
	1052	983	1001	2035	2053	
Uses diesel elec (=1)	0.17	0.21	0.11	0.039	-0.063	1.70
	[0.38]	[0.41]	[0.31]	(0.058)	(0.046)	(0.19)
	1052	983	1001	2035	2053	
Uses own panel (=1)	0.034	0.050	0.061	0.016	0.027*	1.81
	[0.18]	[0.22]	[0.24]	(0.014)	(0.015)	(0.17)
	1052	983	1001	2035	2053	
Uses HPS solar (=1)	0.0067	0.0081	0.0050	0.0015	-0.0017	0.14
	[0.081]	[0.090]	[0.071]	(0.0078)	(0.0054)	(0.87)
	1052	983	1001	2035	2053	

* p lt 0.10, ** p lt 0.05, *** p lt 0.01

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Table 3: Summary of electricity sources, all panels

	Grid	Diesel	Other solar	HPS
	Panel A. Baseline			
Monthly price (Rs.)	153.0	99.76	100.5	N/A
Load (watts)	278.1	146.8	178.8	N/A
Supply hours	7.41	3.38	7.47	N/A
Source available	0.35	0.39	1	0
	Panel B. Endline 1			
Monthly price (Rs.)	118.6	104.8	89.45	163.8
Load (watts)	154.7	118.3	51.57	37.07
Supply hours	6.32	3.08	5.86	6
Source available	0.59	0.13	1	0.65
Ownership of assets				
Mobile and/or bulb	1	1	1	0.93
Fan	0.34	0.04	0.10	0.03
TV	0.11	0.01	0.04	0.02
	Panel C. Endline 2			
Monthly price (Rs.)	N/A	N/A	50.58	200
Load (watts)	N/A	N/A	66.11	N/A
Supply hours	N/A	N/A	N/A	6
Source available	0.77	N/A	1	N/A

Load reported here is based on household survey appliance ownership, and household survey reports of own solar watt ratings. In the model, we apply diesel generator survey data to assign load available to households served by each generator, as well as technical specifications from HPS for panel capacity.

Table 4: First stage electricity, bulb, and mobile phone outcomes

	Light Bulb Ownership (=1)	Daily Hours of Electricity Use	Mobile Phone Ownership	Price of Full Charge (Rs.)
	(1)	(2)	(3)	(4)
Subsidy treat village (=1)	0.15***	0.94***	0.034**	-0.67***
	(0.047)	(0.24)	(0.014)	(0.24)
No subsidy treat village (=1)	0.098**	0.52**	0.022	-0.46*
	(0.044)	(0.20)	(0.013)	(0.23)
Baseline Controls	Yes	Yes	Yes	Yes
Control mean	0.32	1.16	0.88	4.72
Observations	3001	2868	3001	964

Includes baseline electricity source indicators, baseline monthly income, and baseline equivalent of outcome variable controls. Standard errors clustered at the village level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Household welfare impacts

	Respiratory problems (=1)		Standardized test score		Monthly income
	Adults	Children	Reading	Math	(INR '000s)
	(1)	(2)	(3)	(4)	(5)
	Panel A. Reduced Form				
Subsidy treat village (=1)	0.026	0.012	0.11*	0.095	0.18
	(0.021)	(0.0082)	(0.061)	(0.065)	(0.31)
Normal treat village (=1)	0.017	0.0041	0.020	0.071	0.63*
	(0.018)	(0.0082)	(0.061)	(0.062)	(0.33)
	Panel B. Instrumental Variables				
Hours of electricity	0.027	0.014	0.22	0.21	0.15
	(0.027)	(0.012)	(0.24)	(0.23)	(0.35)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Control mean	0.14	0.024	0	0	7.5
Observations	2710	2669	646	637	2692

Test score results are at the child level. Includes baseline electricity source indicators, baseline monthly income, and baseline equivalent of outcome variable controls. Standard errors clustered at the village level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Nested Logit Estimates of Electricity Source Demand

	Nested Logit (1)			
	Source Coefficients			
Monthly price (Rs. 100)	-1.053***	(0.099)		
Load (watts)	-0.007***	(0.001)		
Hours/day use	-1.058***	(0.094)		
	Demand Shifters			
	Grid	Diesel	HPS	Own Solar
Solid roof (=1)	0.517***	0.245**	0.100	0.252***
	(0.083)	(0.122)	(0.130)	(0.096)
Monthly income (Rs. 100,000)	1.864***	0.655	2.479***	1.924***
	(0.571)	(0.737)	(0.901)	(0.592)
Number of rooms	0.090***	0.107**	0.074	0.120***
	(0.030)	(0.043)	(0.049)	(0.032)
Pukka (=1)	0.367***	-0.000	-0.024	0.039
	(0.084)	(0.133)	(0.140)	(0.102)
Agricultural land (=1)	0.177**	0.201*	0.527***	0.409***
	(0.071)	(0.108)	(0.121)	(0.089)
Number of adults	0.103***	0.087***	0.050	0.104***
	(0.021)	(0.032)	(0.031)	(0.022)
Literacy of household head	0.073***	0.068***	0.019	0.006
	(0.017)	(0.024)	(0.027)	(0.020)
Constant	8.029***	3.710***	5.638***	4.602***
	(0.535)	(0.297)	(0.594)	(0.547)
Off Grid Dissimilarity	.742			
	(.055)			
Observations	28996.0			

Table 7: Counterfactual market shares under varying choice sets

	None	Grid	Diesel	HPS	Own Solar
Panel A1. Model fit to actual market shares (All panels)					
Actual	0.57	0.24	0.08	0.04	0.08
Predicted	0.59	0.23	0.06	0.04	0.08
Panel A2. Model fit to actual market shares (Endline 1)					
Actual	0.61	0.25	0.02	0.08	0.04
Predicted	0.53	0.30	0.03	0.07	0.08
Panel B. Grid unavailable					
Solar everywhere	0.67	0.00	0.05	0.25	0.05
No Solar	0.96	0.00	0.06	0.00	0.00
Panel C. Baseline grid availability					
Solar everywhere	0.54	0.17	0.04	0.19	0.07
No Solar	0.76	0.20	0.05	0.00	0.00
Panel D. Endline grid availability					
Solar everywhere	0.47	0.29	0.03	0.17	0.06
No Solar	0.64	0.34	0.04	0.00	0.00
Panel E. Grid available everywhere					
Solar everywhere	0.36	0.48	0.03	0.13	0.03
No Solar	0.42	0.56	0.03	0.00	0.00

Panels A2 through E are based on endline 1 covariates.

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