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Demand for Electricity in a Poor Economy *

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Abstract

Over a billion people do not have electricity and many others have abysmal power supply. Innovation has cut the price of solar photovoltaic panels to that point that off-grid solar power can compete with traditional, grid electrification to light the homes of the rural poor. We collected data over four years in Bihar, India, as the state underwent a transformation that raised electrification rates nearly 40 percentage points. We use a randomized experiment to estimate a demand model wherein households choose between grid electricity, off-grid electricity sources and having no electricity at all. The model yields three findings. First, demand for off-grid solar power is highly elastic, with an elasticity around -3. Second, the value of off-grid solar is much greater when the grid is absent or if the grid were priced at cost, in contrast to the highly subsidized rates in our setting. Third, though at present power is only supplied part of the day, households do not value improvements in supply enough to justify their cost. Our findings rationalize the government offering a low price, low quality bundle of energy services to maximize access.

1 Introduction

The electricity landscape in the rural parts of developing countries is undergoing radical changes. A billion people, mainly in South Asia and sub-Saharan Africa, do not have electricity in their homes. Even in areas near or on the grid, many poor households are not connected, and the supply of power is often abysmal (Lee et al., 2016; Burgess et al., 2019). This state of energy access today may be due to the poor not valuing electricity, or, just as well, to their governments failing to build the grid and supply power.

The transformation has two parts. First, many developing country governments are making huge investments in the traditional mode of electrification, grid extension, and in subsidies for

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household grid connections (International Energy Agency, 2017). Second, rapid declines in the cost of solar photovoltaic panels have opened a second, off-grid mode of electrification CITE NEW FIGURE 1 HERE.[1] Solar panels can be used to supply on the grid, and, unlike other sources of power, can also generate at the same efficiency set on the roof of a single, isolated household. The ready nature and falling costs of solar technology have thus spurred hope of a faster, greener path to universal 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]

This paper studies the value of this wave of electrification for the poor, with an explicit focus on how the poor trade-off electrification via different on- and off-grid sources. Lost in many energy access goals is what kind of electricity the poor themselves want to buy. Solar systems have improved rapidly, yet still leave households in electricity autarky, with higher unit prices and lower loads than available on the grid. Our main contribution is to estimate a demand system to measure household willingness-to-pay for different sources of electricity. We collect a nearly four year panel of data on both the demand and supply sides of the retail electricity market. We combine this data with a randomized-control trial that varies the price and availability of solar microgrids, a new electricity source, and use the experimental variation to estimate demand.

The setting for the study is rural Bihar, India. India, in the last ten years, has contributed XX% of the total net gain in the world in the number of households electrified (International Energy Agency, 2017). Bihar, a state of 104 million, exemplifies these gains: starting from a low rate, we see gains in electrification of nearly 40 percentage points in our sample. In 2013, Bihar's electrification rate was below that in sub-Saharan Africa (World Bank, 2017), many villages in our sample had no electricity at all, and those households with power most commonly bought it from local diesel generators (Figure 1, Panel A). Off-grid power existed but held negligible market share. By 2017, many villages had near-universal electrification,

[1] Universal access to affordable, reliable and modern energy services by 2030 is UN Sustainable Development Goal #7. Goal #7 also targets increasing the share of renewable energy in the global energy mix. Nearly all large-scale aid programs in the power sector include significant on-grid and off-grid components. USAID, for example, launched *Power Africa* in 2013 and DFID launched *Energy Africa* in 2015, both of which invest in off-grid renewable electricity.

[2] "Powering Sustainable Energy for All," *The New York Times*, January 11th, 2012. See also "Africa Unplugged: Small-scale Solar Power is Surging Ahead", *The Economist*, October 29th, 2016.

and solar power from household systems almost completely displaced diesel as the main source of off-grid power (Figure 1, Panel C).

We study the transformation of Bihar's electricity landscape in three steps. First, we introduce a village-level experiment to estimate a demand curve for solar microgrids, apart from any other sources of power. Second, we specify and estimate a demand model, using the experimental variation in price for microgrids as an instrument to recover household willingness-to-pay for electricity. Third, we use the estimated demand over all sources of electricity to value Bihar's electricity transformation and counterfactual changes in grid policy, towards access, pricing and quality.

On the first part, the demand for solar microgrids in the experiment was highly elastic. Demand is nearly zero at the prevailing price of INR 200, but leapt to 17% of households paying for solar at a subsidized price of INR 100, before falling back again, over the course of our experiment. Households in treatment villages were significantly more likely to own light bulbs, use more electricity, purchase more mobile phones and spend less money charging them. Yet, after experimental subsidies were removed, demand for microgrids collapsed.

The experimental estimates are internally valid but leave open *why* households gave up on microgrids. In principle, it could be that households did not find electricity much better than kerosene, or that microgrids were poorly maintained and so deteriorated over time. We argue, using our exhaustive data on other sources, that the collapse in microgrid demand is instead due to household substitution to their own solar systems and to the grid, which the government was massively expanding at the time. With this substitution in mind, it is not possible, from the experimental results alone, to infer microgrid demand in different circumstances, such as if the grid did not arrive during our study, or to measure households' value of electrification from all sources put together.

In the second part, therefore, we specify and estimate a model of household demand over all electricity sources. The model is a discrete choice demand system (McFadden, 1974; Lancaster, 1971). We allow the unobserved quality of all electricity sources to vary without restriction across villages and time (Berry, 1994). In our setting, this feature is essential, since we expect that source quality is changing over time, and it would be hard to observably capture how, for example, the government's greater efforts to hold camps and sign up new households for infill grid connections translated into lower connection costs. We estimate the model in our household-level panel data, allowing different households to have preferences over grid electricity, common diesel generators, solar microgrids, their own solar systems and no electricity as possible sources. As in the discrete choice literature (Berry, Levinsohn and Pakes, 1995, 2004), we estimate the model using instrumental variables to account for the likely endogeneity of price to quality. We use the experimental treatment assignments as instruments, and show that this strategy is essential to recovering unbiased estimates of demand. Ordinary-least squares estimates of the price elasticity of demand are negative but small and not significantly different from zero, whereas our experimental IV estimates are greatly more negative, significant and stable across specifications.

The demand estimates show substantial heterogeneity in household preferences over electricity sources. There are two main findings from the demand parameters themselves. First, household demand for off-grid solar electricity is highly price sensitive, with an elasticity around -3. Second, richer households, by any measure, prefer grid electricity. For example, a representative poor household has a baseline 21 percent probability of choosing grid electricity. If the household had a solid roof, but otherwise similar assets and income, the probability of choosing grid electricity would increase by 11 percentage points. This greater preference for the grid makes sense, since the grid can support higher load appliances like fans and televisions that richer households demand. In the model, therefore, off-grid electricity is a stop-gap technology, occupying the product space between no electricity and the grid.

The demand model allows us to measure the gains from electrification. We run counterfactuals that vary the supply side of the rural electricity market on three different dimensions: (i) technological innovations make solar systems cheaper, (ii) the reach and quality of grid electricity is improved and (iii) the government changes grid pricing and quality from the low price, partial supply status quo.

We find that the advent of off-grid solar power, from being out of the market to 2022 projected prices, increases the surplus of households by 1.5% of median household income. Using the model, we study how the surplus from solar depends on the availability of the grid. Solar power is roughly twice as valuable to poor households when the grid is absent. Solar power off the grid also has an ancillary beneficiary: the government utility. The government loses money on every rural customer it serves. Therefore, by inducing households to substitute away from the grid, the advent of solar power reduces government losses on electricity supply by nearly one-third.

Grid electricity contributes only slightly more to household surplus, for our study population, than does solar power. We find that grid electrification of all sample villages raises household surplus by INR 1326 (USD 22) per household per year, or 1.8% of median household income. The value of grid electrification depends critically on current grid prices being highly subsidized. If the price of the grid were raised to cover cost, grid market share would plummet, from 24% to 5%. The corresponding drop in household surplus is nearly as large as would occur from removing the grid altogether—a grid priced at cost might as well not exist for this population. Conversely, improvements in quality, such as by ensuring that the grid supplied for all five peak hours every evening, would increase household values for the grid and draw some more households (5 percentage points) to get connections.

Finally, we use the model to address why the government chooses to offer a particular low price, low quality bundle of energy services. The grid supplies power for 11 hours a day, on average, and only XX hours during the key evening peak. We consider a counterfactual, budget neutral "grand bargain," in which the government supplies power for all the peak evening hours but raises prices about a quarter to cover the cost of the additional energy supplied. We find that such a bargain would slightly lower total surplus and household surplus, and differentially lower household surplus for consumers below the poverty line.

The results suggest that the government is facing a hard series of choices in electrification: few poor households value grid electricity enough to pay for it if priced at cost, nor do they value continuous supply enough to pay for an upgrade, relative to the patchy supply today. To say tariffs should be reformed to improve grid quality is a facile recommendation, and not supported by our results. Solar power, by providing a stop gap technology, makes achieving high rates of electrification—defined as the use of electric light and mobile phone charging, from any source—easier, and dulls some of these trade-offs, as households priced out of the grid fall back to solar. Over time, since richer households prefer the grid to run higher load appliances, we would expect households to transition to the grid rapidly as incomes rise.

Our paper contributes to the literatures on the effects of electrification and demand for electricity connections. Much of the literature on rural electrification has focused on the spread of grid electricity, and found that grid electrification has had large effects on labor supply, productivity and welfare.[3] There are also a handful of experiments on the demand for electricity connections, including at least two experiments on demand for off-grid solar power.[4] The impact analyses in these papers are broadly consistent with our finding that demand for off-grid solar is highly price elastic.

Our paper takes several steps to unify the literature on electricity access for the poor. First, we estimate how households value both grid and off-grid electricity together, in a single demand system. Prior work considers each source in isolation, and so cannot study substitution between sources, which is ubiquitous in places at the frontier of electrification today. Second, we consider the effects of policy on the supply side towards access, pricing and quality. Our results rationalize a seemingly dysfunctional rural electricity sector, by showing that increasing price and quality as a bundle may be less preferred by the poor households that governments are trying to serve. The present subsidies and low quality can be justified by a government that values access for the rural poor above all.

Our study also contributes methodologically to the development literature by placing a greater emphasis on the external validity of experimental results. Field experiments have lately gotten longer to address the realism and durability of effects.[5] A growing body of work uses experimental variation to help estimate structural models.[6] We run a medium-run experiment that varied village-level prices over nearly four years and collect data on both sides of the market. We use our experiment to estimate the price elasticity of demand for electricity in a discrete choice demand model. The model estimates enable us to study policy counterfactuals that are well beyond the boundaries of the experiment itself, though not so

[3] Dinkelman (2011) finds that electrification increases employment but may have lower female wages, perhaps by substituting for women in household work. Rud (2012) shows that electrification leads to structural transformation. Intermittent supply of electricity reduces manufacturing firm output (Allcott, Collard-Wexler and O'Connell, 2016). Lipscomb, Mobarak and Barham (2013) find large effects of electrification on the UN Human Development Index and average housing values. Barron and Torero (2017) find that household electrification reduces indoor air pollution. Burlig and Preonas (2016) find small and statistically insignificant effects of India's flagship village-level electrification program on the employment and wealth of households in marginally electrified villages.

[4] A recent experiment in Kenya finds that grid electrification is prohibitively costly for rural Kenyan households even at heavily subsidized prices (Lee, Miguel and Wolfram, 2016). 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 socioeconomic 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.

[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. Bandiera et al. (2017) study a 7-year follow-up to an asset transfer program.

[6] Prominent examples estimate models of education, labor supply and migration (Attanasio, Meghir and Santiago, 2011; Duflo, Hanna and Ryan, 2012; Bryan, Chowdhury and Mobarak, 2014; Galiani, Murphy and Pantano, 2015).

far beyond the boundaries of our data, during a period of transformative change.

The rest of the paper runs as follows: Section 2 describes our data and gives background on electrification in Bihar. Section 3 introduces the solar microgrid experiment and presents estimates of the demand for microgrids alone. Section 4 then lays out and estimates a demand model over all electricity sources. Section 5 uses the demand model for counterfactual analysis. Section 6 concludes.

2 Background and Data: The Electricity Landscape in Bihar

The study is set in Bihar, an Indian state of 104 million (Census of India, 2011), about the population of Ethiopia or the Phillipines. Bihar is one of India's poorest and least electrified states. Table 1 juxtaposes the United States (column 1), India (2), sub-Saharan Africa (3) and Bihar (4) on the dimensions of per-capita GDP, per-capita electricity consumption and access to electricity circa YEAR. The electrification rate in Bihar at the beginning of our study was only 25%, about one-third of the all-India rate of 79% and below the rate of 37% in sub-Saharan Africa.

The average Bihari used just 122 kWh of electricity per year. The per capita electricity consumption is less than one percent of the level in the United States (column 4, last row), roughly in line with the disparity in nominal per capita income. At this low level of consumption, which averages over many households with no electricity at all, an individual can power two light bulbs totaling 60 watts for six hours per day year round. The low level of average consumption is an equilibrium outcome. Demand for electricity is low because many households are poor. Supply of electricity is limited, on both the extensive margin, since many villages are not on the grid, and the intensive margin, since supply is rationed.

In response to persistently low rates of household electrification in states like Bihar, the Government of India has lately funded two large campaigns for village-level grid extension and household-level connections, respectively. In his 2015 independence day address, Indian Prime Minister Narendra Modi launched a rural electrification program with an ambitious 1,000-day deadline to electrify 18,452 census villages still without access, at an estimated cost of USD 11 billion.[7] The village-level goal was declared achieved ahead of schedule on April 28, 2018.

[7]The target is out of a total of almost 600,000 census villages in India. This program, the Deen Dayal Upadhyaya Gram Jyoti Yojana (DDUGJY), is a continuation, under a new name, of the prior government's

When the grid reaches a village poor households may not connect or take a long time to do so.[8] The federal government therefore started a complementary USD 2.5 billion program to subsidize infill household connections in electrified villages.[9] Even with money, states have to execute to provide connections, since nearly all grid electricity in India is supplied by state-run utilities. Bihar has made electricity access a priority (Kumar, 2019). Nitish Kumar, Bihar's six-time Chief Minister, promised universal household electrification as part of his reelection campaign (Business Today, 2017).

Our study was perfectly timed to capture the disruption that this big push for rural electrification caused in Bihar's electricity markets. Here we first introduce our data sources and then use that data to describe the electricity market in Bihar and its remarkable transformation during our study period.

a Data

We collect data from both the demand and supply sides of the market over a nearly four-year period. There are four main sources of data. First, on the demand side, a three-wave household panel survey on the sources and uses of electricity. Second, on the supply side, administrative data on customer enrollment and payments from a provider of solar microgrids. Third, on the supply side, survey data from the operators of common diesel generators, an important off-grid source of electricity. Fourth, on the supply side, administrative data from the state utility on customer billing and payments as well as electricity supply. We were running a separate, contemporaneous project with the state utility that allowed us to gain access to this data. The timing of collection for each source of data is illustrated in Appendix Figure A1. The first and last survey waves are separated by nearly four years and the supply-side data is also collected over several years.

Our study sample consists of 100 villages distributed across three districts in Bihar (Figure 1). The study villages were chosen to have low rates of electricity access, along three criteria. First, they were not listed as electrified villages by the government, meaning that at least one neighborhood of the village was not on the grid, and generally implying low rates

Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY), which had similar objectives but fell short of reaching all villages (Government of India, 2015; Burlig and Preonas, 2016).

[8]A village is defined as electrified once public spaces, such as schools and health centres, have access to electricity, along with a minimum of 10% of its households.

[9]The Pradhan Mantri Sahaj Bijli Har Ghar Yojana, known as Saubhagya, launched in September 2017.

of household grid electrification. Second, as we worked with a solar microgrid provider, Husk Power Systems (HPS), to offer solar microgrids, villages must not yet have been offered HPS microgrids. Third, to enable a possible expansion of microgrids, villages were chosen to be reasonably close to existing HPS sites. The total population of households in all 100 villages was 48,979. Within this sample, we collect data for all of the sources above either at the village level (diesel and grid supply) or the household level (household survey, microgrid and state utility payments). We now describe each of these data sources in greater depth.

Household panel survey. Our household panel survey sampled 30 households per village to cover about three thousand households across the 100 sample villages. The sample was drawn to represent those with an interest in a microgrid solar connection, but, because this screening for interest was loose, in practice the sample is nearly representative of the population as a whole.[10] The survey has three rounds, two thick rounds, which we call baseline and endline, and one thin round, which we call follow-up. The baseline survey took place in November and December of 2013, the endline from May to July of 2016, and the follow-up in May 2017 (See Appendix Figure A1).

The two thick rounds used nearly the same survey instrument and covered demographics, the sources and uses of electricity and welfare outcomes likely to be influenced by electricity use. There are three main kinds of variables. First, demographics and household characteristics, such as household size and literacy, as well as various wealth proxies, such as income, size and structure of house and ownership of agricultural land. We use these variables to predict electricity demand. Second, variables on electrification status, sources of electricity, source characteristics such as hours of supply, payments, and uses of electricity including a complete appliance inventory. Third, variables on education and health. We gave children reading and math tests and asked households about any respiratory problems.[11]

The thin, follow-up survey round took place one year after endline. The purpose of this round was to update household sources of electricity. This round therefore did not update

[10] We ran an initial customer identification survey in August 2013 across all sample villages, which elicited household willingness to pay for a solar microgrid connection. A random sample of 30 households per village was selected among those who expressed interest in paying for a solar connection at a monthly price of INR 100. This identification was barely restrictive in practice, because households were not required to put down a deposit nor where they held to their initial statement of interest when the product was later offered. Over 90% of households without electricity or with just diesel-based electricity said they would be interested in using microgrids. The same was true for over 70% of households with a grid connection or home solar panels.

[11] Prior research suggests that substituting from kerosene to electricity reduces indoor air pollution (Barron and Torero, 2017). It has been widely hypothesized that children may benefit from using electric light to study CITE.

household characteristics or education and health outcomes.

Microgrid administrative data. The second source of data is an administrative dataset on microgrid customers from HPS. We partnered with HPS to roll-out solar microgrids in the sample villages experimentally (See Section **??**). The dataset includes enrollment, pricing and customer payments from January 2014 to January 2016. This data was subsequently matched with that collected in our household surveys in order to estimate demand for solar microgrids during the time between our survey waves.

State utility administrative data. We use three datasets pertaining to grid electricity: (i) a consumer database for all formal customers, (ii) a billing and collections dataset containing bills and customer payments, and (iii) village-level hours of supply, recorded from administrative log-books. The data sources (i) and (ii) are matched at the customer level to our survey respondent households. Many households using the grid in the survey are not matched, as there are high rates of informal connections, i.e. electricity theft, in Bihar. We define formal connections as those where surveyed households provided valid customer IDs that we could match to the administrative data, and call households informal if they could not provide an ID (which is written on the electricity bill) or the ID did not match. We discuss the characteristics of formal and informal households below, when describing the characteristics of grid electricity.

Survey of diesel generator operators. Our final source of data is a survey of diesel generator operators. Entrepreneurs set-up diesel generators and wire customers within non-electrified villages, providing electricity to fifty or more households at a time. We surveyed these operators to collect data on operating costs, hours of operation, pricing and customers served from January 2014 to 2016.

With these sources of data we see, on the demand side, a rich set of household characteristics and the actual sources and uses of electricity, in terms of the energy services that connections provide. On the supply side, we have data on all the competing sources in the marketplace, either directly from administrative sources or indirectly from our household survey of electricity consumers.

b Sources of electricity

Electricity is a prototypical commodity but in Bihar electricity connections are differentiated products. This section describes the characteristics of different electricity sources. Unless otherwise specified, we describe source characteristics at the time of our baseline survey.

i Grid electricity

Table 2 reports the characteristics of electricity sources at baseline (Panel A), endline (Panel B) and follow-up (Panel C). The main source of data is the household survey. Grid supply hours are recorded from the administrative data.

Grid electricity, the traditional mode, has a desirable bundle of characteristics. The grid price of INR 73, the mean monthly payment reported by grid-connected households, is roughly tied for the lowest price of any electricity source (Panel A). Households on the grid have a mean connected load of 322 watts, twice as large as any other source (Panel A).[12] This greater load is due to ownership of more and larger appliances (Panel B). One-third of grid-connected households own a fan and one-tenth a television, whereas the ownership of these appliances for households using other electricity sources is much lower or negligible. By contrast, nearly all surveyed households with any source of electricity plug-in mobile phones and light bulbs (Panel B).

We take the grid "price" to be the self-reported monthly payment, averaged across formal and informal customers, of INR 73 per month. Due to low rates of billing and collection, and high rates of informality and theft, this *de facto* price is only 46% of the *de jure* price, which we calculate, using the administrative tariff schedule and consumption data, to be INR 150 per month.[13] The presence of informality acts as a large price cut for the grid. Of the 158 households using the grid at baseline, less than half answered yes to the question "Do you pay electricity bills?" The full grid price of INR 150 per month would place it amongst the most costly sources; at INR 73 per month it is one of the cheapest.

CC: I don't understand the above. Many households are formal but do not pay their bills. Therefore if half of households are not formal, and pay zero, and half of households are formal, and pay generally less than 100%, the average of their payments should be less than 50%.

[12] Properly, connected load is not a characteristic of a source, but depends on household appliance purchases. We describe connected load as if it were a source characteristic because the connected load for all sources but the grid is effectively limited by the load a source can serve.

[13] Tariffs are determined for each household by their consumer category. Many households in the sample qualified for the Kutir Jyoti program, a lifeline tariff for the poor. The KJ program has a flat rate monthly tariff of INR 55-60 for unmetered households and a rate of INR XX for metered households. Households on the regular domestic category are charged a flat rate of INR XX per kWh if unmetered or a rate of INR XX per kWh if unmetered. Given the tariff composition of our sample and an estimated average consumption of XX per month, we expect households' bills would average INR 150 per month if they paid the full bill every month.

Burgess et al. (2019) study the origin and consequences of below-cost pricing for electricity in developing countries, and treat Bihar as an in-depth case study. We argue that the tolerance for theft and low *de facto* prices should be viewed as a delibrate government policy to maximize access, subject to technical and political constraints, and often at the expense of quality and reliability. The government loses money on every customer served. Supplying power below cost to increase access requires the government to ration electricity in order to limit their financial losses. Appendix Figure CITE shows the distributions of hours of supply for the grid, during the peak hours of five to ten in the evening and the off-peak hours. In the study area mean hours of grid supply was 9.7 hours at baseline, higher than for any other source. However, mean supply on peak—in the evening when households are at home and demand power for lighting—was only XX hours per day, less than several alternatives.

ii Diesel

Diesel generators are too big for households on their own. Entrepreneurs buy generators and wire villages to supply diesel power on fixed-price plans during the high-demand evening hours. Table 2, Panel A shows that diesel generators have a mean price of INR 100 per month, which is cheaper than the full price of the grid but a third more expensive than the effective grid price. The modal diesel plan offered, by far, was a 100 watt connection (enforced by wiring a fuse onto the service line) for INR 100 per month. The 100 watt load is sufficient for consumers to power several light bulbs and charge mobile phones. Generators run on a predictable schedule in the evening and early night-time for an average daily supply of 3.4 hours.

iii Own Solar

Households in all villages have the option of buying their own solar systems in private markets. A system consists of a panel, a battery, and sometimes a socket or controller to plug in and switch appliances. We refer to this source as "own solar" to distinguish it from solar microgrids that serve several households together. Households pay for own solar systems up front and would usually to travel to a larger market town to buy a system and bring it back to the village. Any household could do so, so we assume own solar is available in all villages. The characteristics of own solar make it a close substitute to diesel electricity. Own solar systems have a similar price to diesel and power appliances of similar connected load.[14] Solar systems at baseline run 8 hours per day, longer than for diesel generators but somewhat less than the grid.

iv Microgrid Solar

A solar microgrid has the same basic components as an own solar system but a slightly larger scale, serving six to nine households at a time. Households can therefore only connect if they also have interested neighbors (as with a diesel generator, but much more locally). The microgrids offered by HPS consist of a 240 watt panel and a separate, 3.2 volt rechargeable battery and meter for each household. Households have a key pad to secure access to the battery and must purchase codes on a monthly basis to keep using the system. Each household on the microgrid gets 25 to 40 watts of power for 5 to 7 hours per day. This represents a small quantity of power, but the system is bundled with two high-efficiency light bulbs and an electrical outlet, typically used for mobile phone charging, and therefore provides very similar energy services to diesel and own solar systems (Table 2, Panel B). Because of its low voltage, the microgrid is unable to power small appliances such as fans, unlike diesel and some own solar systems. The prevailing price of microgrids at the start of our study was INR 200, making the microgrid the most expensive source of electricity, but this price came down to INR 160 and and was further cut as a part of our experiment (Section **??**).

c Bihar's electricity transformation

Competition between the above electricity sources transformed the electricity landscape in Bihar during our study. The electrification rate, from any source, increased 37 percentage points, from 27% to 64%, in somewhat less than four years.[15] Figure 2 maps this transformation with the market shares of different electricity sources village-by-village; Figure 3 gives aggregate market shares by source and survey wave; Figure 4 breaks out these market shares by household income.

Start with Figure 3. Bar heights are market shares. Each cluster of bars shows a source of

[14] Once purchased, own solar systems have no operating costs. To make the price comparable to other sources, which are paid monthly, we amortize the capital costs of own solar using an assumed lifetime of seven years and 20% interest rate.

[15] As a point of comparison, the same increase for rural (farm) households in the United States took 9 years, during and after World War II, from 1939 to 1948 (of the Census, 1975).

electricity and the shadings of bars represent shares at different points in time (survey waves). At the baseline survey, shown by the black bars, the largest source of electricity, with 17% household market share, was diesel power. That share understates diesel's appeal; because diesel operators require a sufficient number of customers to support their fixed costs, diesel was only available in 62% of villages at baseline (Table 2, Panel A). The grid, by its characteristics, seems better than diesel, but was available in only 35% of villages (Table 2, Panel A) and held just a 5% market share (Figure 3). Microgrid solar had not entered and own solar systems, being relatively new, also had only a 5% share. Figure 2 shows the distribution of these market shares across villages. Many villages are black or nearly all black, with a small amount of red, for the grid, and a decent share of blue, for diesel.

From this base, there are two transformative changes in market shares, and one passing change. The transformative changes are first, rapid leaps in grid market share from 5% to 25% and then 43% and second, a delayed rise in own solar market shares from 5% at baseline to 15% at follow-up. The grid electrification rate doubled in the one year between our endline and follow-up surveys. The red and yellow circles of Figure 2, Panel B show the growth in grid and solar electricity, respectively, across a wide set of villages. These two changes, together, cut the rate of households without any source of electricity sharply (Figure 3, right-hand cluster of bars). They also crushed the share of diesel, from 17% to a paltry 3%. Diesel operators exited many villages altogether (not reported ADD APPENDIX FIGURE). The passing change is that solar microgrid share went from nothing, up to 9%, when subsidies were offered during our experiment, and then fell back to 3% a year later. Thus microgrids gained market share but were not mainly responsible for the transformation in electricity access in Bihar.

To a first approximation, these huge shifts in market shares should be thought of as shifts out in supply and electricity access for both the grid and own solar. The government, under the electrification programs described above, extended the grid from 35% to 76% of sample villages, held camps to connect more households and heavily subsidized connections, including complete subsidies for all households designated Below the Poverty Line (BPL). No villages in our sample had grid take-up over 50% at baseline, but there were 44% did by the follow-up survey.

A second disruption to rural electricity markets has been caused by global declines in the cost of solar technologies. The US National Renewable Energy Laboratory projects a 55%

reduction in the cost of solar photovoltaics and a 75% reduction in the cost of batteries from XXXX to 2022 (Feldman, Margolis and Denholm, 2016). Our data reflects these trends. The price of own solar systems fell 11%, from INR 74 at baseline to INR 66 at follow-up. An important caveat is that this price is likely not for the same energy service, but a better one. Solar vendors may have penetrated smaller towns closer to villages, effectively lowering connection costs, and batteries may be more reliable. We return to discuss source quality with the demand model estimates.

While large shifts in supply are needed to explain the rapid growth in electrification, there is also significant heterogeneity in household demand, even within a village. Figure 4 plots electrification rates in a stacked bar chart. Each colored bar segment refers to a different source of electricity, or is black, for no electricity. The three clusters of bars correspond to our three survey waves. Within each cluster, the bar on the left gives the market shares for households in the poorest income quartile in our sample, and the bar on the right for households in the richest income quartile. The richest quartile has twice the electrification rate as the poorest quartile at baseline. The composition of sources, for the rich, is also tilted towards solar systems, though diesel (blue segment) has the largest market share for both income quartiles. By the endline survey (middle cluster), electrification rates increase about 10 percentage points for both income quartiles, and there is a large compositional change, as the grid knocks out diesel generators. Microgrids (green segment) also gain market share. By the follow-up survey (rightmost cluster), the electrification rate for the poor, at 60%, exceeds the rate for the rich from the prior survey wave. The relative gap in electrification rates is much smaller and the composition of sources is similar for both quartiles; solar, in particular, is no longer a product for the rich. While survey-measured household income is only one proxy for electricity demand, these comparisons suggest that there is significant household-level heterogeneity in demand for electricity sources.

The electricity upheaval in Bihar therefore had two main features. First, a broad surge in access, driven by expansion of the grid and a fall in the cost of solar. Second, a huge compositional change, due both to government policy and technological innovation. We proceed to estimate household demand for electricity sources in order to value how these changes in the market have benefited households.

3 Demand for Solar Microgrids

This section describes the design and results of the experiment we use to estimate the demand for solar microgrids. The estimates of microgrid demand are important in their own right. Off-grid solar technology has emerged as a widespread substitute for grid electricity in marginally electrified areas, and estimating demand for this new good will allow us to value how much it benefits the poor.

The microgrid demand estimates also serve an instrumental purpose. In the next section we will estimate a demand model over all electricity sources. The key parameter in that demand model is how sensitive households are to the price of a source. We use the microgrid experiment, described here, as an instrument for electricity prices to estimate our demand model. Using the experiment to vary price builds a transparent connection between the reduced-form and structural estimates of demand.

a Experimental Design

We partnered with Husk Power Systems (HPS) to vary the availability and price of solar microgrids in a randomized control trial. HPS was founded in 2007 to provide electricity in rural areas using biomass gasifiers as generators to obtain 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 broad and were subject to fuel supply disruptions. HPS made a strategic decision to add a solar microgrid product to its portfolio as a means of reaching a wider set of customers.

The experimental design is a cluster-randomized control trial at the village-level. We randomly assigned sample villages into one of three arms: a control arm (34 villages) in which HPS did not offer microgrids, a normal price arm (33 villages) in which HPS offered microgrids at the prevailing price of INR 200 per month and a subsidized price arm (33 villages) in which HPS offered microgrids 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 only this experimental arm, down to INR 160, due to a lack of demand at the higher price. The normal price arm can be thought of as providing the service roughly at cost and the subsidized arm perhaps 40% below cost.[16] Within each treatment village, all households were offered the same HPS connection and pricing, regardless of whether they had previously expressed interest in HPS's product or participated in our baseline survey. Sales of solar microgrid connections began in January 2014, right after the baseline survey.

Table 3 shows the balance of covariates in our baseline survey across treatment and control arms for demographic variables (Panel A), wealth 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 square brackets. The next two columns show the differences between normal price and control arms and between subsidized price and control arms, respectively, with standard errors in rounded brackets. The final column shows the F-statistic and p-value from a test of the null hypothesis that the differences in means between normal price and control arms and between subsidized price and control arms are jointly zero at baseline.

The joint test rejects the null of equality of treatment and control arms at the 10%-level for three out of twelve variables at baseline. For example, households in subsidy villages are more likely to have solid or *pukka* houses than control households and to have solid roofs. The overall rate of electrification does not differ by experiment arms (an F-test for the joint equality of "Any elec source (= 1)" across treatment arms has p-value 0.54), 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 household covariates as controls in both our reduced-form and structural estimates.

Because of the sample selection criteria, we are working with a population that is poorer than the population of Bihar as a whole. Self-reported household incomes in the control group at baseline averages INR 7,460 per month (USD PPP 2.6 per person per day), compared to state per capita income of XXXX per month CITE. Two-thirds of households own agricultural land and about a quarter have a *pukka* house, which is constructed of a solid material like brick. The average household has 3.3 adults living in 2.4 rooms.

[16]We estimate the capital and installation costs of a microgrid to be INR 105 per household per month (Figure E2). This figure is net of capital subsidies provided by the government, which were on the order of 60% in 2014. The service of the system would include additional costs for billing, collection and maintenance. It is therefore reasonable to estimate cost in the range of INR 160 to INR 200 per month, the range of prices offered in our normal price arm.

b Results

The main energy services that microgrids provide are lighting and mobile phone charging; households without electricity generally use kerosene for lighting and pay shopkeepers or neighbors a piece rate to charge their phones. Appendix B shows that households in treatment villages used more electricity, own light bulbs and mobile phones at higher rates and pay less to charge their phones. Microgrids therefore provide the basic energy services they promise.

We use the experiment to estimate the demand for solar microgrid connections. In the administrative data, we observe household decisions on whether to pay for their microgrid each month. Households that did not pay would be disconnected, eventually, but from month to month this risk was low.[17] We use payments for the service at different time horizons as the measure of quantity demanded.

Willingness-to-pay, that is, demand, is a summary measure of household surplus from energy services. An objection that can be raised to using household demand as a summary outcome is that there may be intra-household benefits to electricity access that are not captured by demand. Leading candidates for such benefits include additional evening study time for children or improved indoor air quality, from reduced use of kerosene Barron and Torero (2017). We collected data on a range of social welfare measures, including children's study time, children's test scores, and self-reported respiratory distress. While households in treatment villages used more electricity, we do not see any statistically significant improvements on these welfare measures.[18] Appendix B describes this analysis. Given that we do not find any intra-household benefits of microgrids, beyond the direct use of energy services, we proceed with willingness-to-pay as our main outcome measure.

Figure 5 plots the share of households that chose to pay for microgrid electricity at different prices and over different time intervals. Each 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 survey at month 29. Three features of demand stand out. First, the demand for microgrid electricity at the normal price prevailing before the experiment is practically zero: only about 2% of households paid even a single month at this price. This feature means that

[17] 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.

[18] The main caveat to this result is that, due to low take-up of microgrids in the higher price arms, we are underpowered for test score outcomes and could not reject fairly large positive effects.

we effectively observe the choke price, the price beyond which no households buy microgrids. Thus we do not have to extrapolate out of sample to calculate how much consumers may value microgrids at higher prices. Second, demand is highly elastic, as evidenced by the fact that the microgrid share increased to 17% at INR 100 per month, in the subsidized price arm. Recall from the baseline data that INR 100 per month is by far the most common price charged by diesel generators, so this price makes solar competitive with existing off-grid sources. The price sensitivity we find for solar microgrids agrees with other work that finds demand is close to zero when off-grid solar is priced at cost (Aklin et al., 2017; Grimm et al., 2016).

The third notable feature of demand is that it collapsed over the course of the experiment. By the time of the endline survey, about two and a half years in, demand at the subsidized price fell from 17% to 7% of households, and at the normal price from 7% to zero. This collapse, in isolation, would be consistent with several explanations. Electricity might be an experience good that households discovered was no better than kerosene. Microgrids may have been poorly maintained, leading to growing disuse over time (As Hanna, Duflo and Greenstone (2016) find for cookstoves). There may have been a temporary aggregate demand shock for electricity during our study (Rosenzweig and Udry, 2019).

The descriptive evidence from Section 2, however, argues that these explanations are needlessly subtle: microgrids lost market share because the rapid expansions of own solar and the grid ate their lunch. The main concern with the reduced-form estimate of experimental demand, therefore, is that it is internally valid, but too narrow. Households may value electricity, but not microgrids, if other substitutes are available. Moreover, as a matter of external validity, household demand for the microgrid product would have been different, perhaps drastically so, if households faced a different choice set, for instance if the government had not made a "big push" with the grid. The next section therefore introduces a model to jointly estimate household demand for *all* sources of electricity.

4 Model of Demand for All Electricity Sources

We model consumer demand for electricity using a discrete choice demand model over electricity sources. We specify a nested logit model (McFadden, 1978, 1980; Goldberg, 1995).

Several aspects of our empirical setting allow for an especially rich specification of the model and credible estimation of its parameters. First, we have a household-level panel survey, and therefore allow demand to depend on both source and household characteristics. Second, we allow the unobserved quality of all electricity sources to vary without restriction across villages and time (Berry, 1994). In our setting, this feature is essential, since we expect that source quality is changing, and it would be hard to observably capture how, for example, the government's greater efforts to hold camps and sign up new households for infill grid connections translated into lower connection costs. Third, we observe one hundred separate markets over time, and experimentally vary the price of one product, microgrids, across markets. The experiment allows us to estimate a key parameter in the model, the sensitivity of households to monthly prices. To the best of our knowledge, this paper is the first to use an experiment to estimate a discrete choice demand model.[19]

a Specification

Utility for household i in village v from electricity source j in survey wave t is is given by

$$\begin{aligned} U_{ijtv} &= \delta_{jtv} + z_{it}'\gamma_j + \epsilon_{ijt} && (1) \\ &= V_{ijtv} + \epsilon_{ijt}. && (2) \end{aligned}$$

The term V_{ijtv} is the strict utility of a choice for a household absent their idiosyncratic taste shock ϵ_{ijt}. The vector z_{it} contains observable household characteristics including the number of adults, household income, whether the household owns agricultural land, the literacy of the household head, the number of rooms in the house, and the solidity of the house and the roof. These characteristics enter utility with a choice-specific coefficient γ_j, which captures how household observables shift mean utility relative to the mean for that source, village and survey wave. For example, as income increases, households may have a greater preference for grid electricity $\gamma_{j=grid} > 0$, but an unchanged preference for diesel.

The term δ_{jtv} represents the mean utility of an electricity source j in village v at survey wave t and depends on observable source characteristics x_{jtv} and unobserved quality ξ_{jtv}

$$\delta_{jtv} = x_{jtv}'\overline{\beta} + \xi_{jtv}. \tag{3}$$

[19] Kremer et al. (2011) is a close precedent that experimentally varies the quality of a good (a local water source) and uses observable variation in walking distance to water sources as a proxy for price.

The vector $\mathbf{x}_{jtv}$ of observable source characteristics includes price, hours of supply on-peak (from five to ten pm), and hours of supply off-peak. Quality ξ_{jtv} is the unobservable source-specific utility in a given village and at a certain time. Quality may include both unobservable physical characteristics, such as the load that can be served by a solar system, as well as characteristics of the service, such as service interruptions or the cost of paying a bribe to get a connection in the first place.

The nested logit model imposes that households' idiosyncratic tastes for electricity sources are distributed iid across households and survey waves with the joint distribution

$$F(\epsilon_{i1t}, \ldots, \epsilon_{iJt}) = \exp\left[-\sum_{g} \Big(\sum_{j \in \mathcal{J}_g} e^{-\epsilon_{ijt}/(1-\sigma_g)} \Big)^{1-\sigma_g} \right].$$

Each electricity source j belongs to a nest, indexed by g. The parameters σ_g measure the similarity of sources within a nest; as σ_g approaches one, idiosyncratic variance in utilities comes mostly from the nest level, not from distinctions between sources within a nest. Under the restriction $\sigma_g = 0$ there is no within-nest correlation and the model becomes a multinomial logit model.

The choice probabilities in the model take a simple form. The inclusive value of nest g,

$$IV_{igtv} = \ln \sum_{j \in \mathcal{J}_g} e^{V_{ijtv}/(1-\sigma_g)},$$

gives the expected indirect utility when maximizing utility across sources in nest g (up to an additive constant). The probability of i choosing a source j in nest g_j is then

$$\Pr(y_{it} = j | z_{it}) = \frac{e^{V_{ijtv}/(1-\sigma_{g_j})}}{e^{IV_{igt}\sigma_{g_j}} \sum_g e^{IV_{igtv}(1-\sigma_g)}} \tag{4}$$

Choice probabilities differ by household because they depend on household characteristics z_{it} via the V_{ijtv}. Market shares in the model are defined as the sum of household choice probabilities across households in a village.

b Estimation

We estimate the model in two stages. The first, nonlinear stage estimates the parameters of equation 1 via maximum likelihood. The second, linear stage estimation uses the $\hat{\delta}_{jtv}$ from the first stage as the dependent variable to estimate equation 3 using two-stage least squares. This two-step procedure is common in the estimation of random coefficients logit models (Berry, Levinsohn and Pakes, 1995, 2004). The key idea is to invert market shares to solve for mean indirect utilities, allowing for linear IV estimates that are unbiased in the presence of the endogeneity of price to quality (Berry, 1994).

Nonlinear estimation of the first stage. In the first stage, we use maximum likelihood to estimate the parameters δ, γ and σ using equation 4. Let y_{itj} indicate that household i in survey t chose product j. The log-likelihood of the sample is

$$\log \mathcal{L}(\gamma, \sigma | y, z) = \sum_{i=1}^{N} \sum_{t=1}^{T} \log \Pr(y_{itj} | z_{it}; \gamma, \sigma, \delta(\gamma, \sigma)). \tag{5}$$

We write $\delta(\gamma, \sigma)$ to show that we concentrate the δ parameters out of the log-likelihood (Berry, Levinsohn and Pakes, 1995). For every candidate parameter vector (γ, σ) we solve for the δ that exactly fits the aggregate market shares.[20] This greatly reduces the dimensionality of the non-linear search, as the δ vector has up to 1200 elements ($= 4$ sources $\times$ 100 villages $\times$ 3 surveys) if every source were available in every village.

Linear estimation of the second stage. We can now use equation 3 to recover the $\overline{\beta}$ parameters via a linear regression of the estimated $\widehat{\delta}_{jtv}$ on the observable characteristics of the electricity source at the survey-by-village level, $\mathbf{x}_{jtv}$. Let $\xi_{jtv} = \overline{\xi}_{jt} + \tilde{\xi}_{jtv}$ be the sum of a survey-wave average quality $\overline{\xi}_{jt}$ for each source and the deviation $\tilde{\xi}_{jtv}$ of the quality of a source in a village from that average. Let T_{Normal} and $T_{Subsidized}$ be village-level treatment dummies. We specify the estimating equations

$$\begin{aligned} \widehat{\delta}_{jtv} &= \sum_{k \neq price} x'_{jtvk} \overline{\beta}_k + x_{jtv,price} \overline{\beta}_{price} + \overline{\xi}_{jt} + \tilde{\xi}_{jtv} && (6) \\ x_{jtv,price} &= \pi_0 + \pi_1 T_{Normal} \mathbf{1}\{Endline\} + \pi_2 T_{Subsidized} \mathbf{1}\{Endline\} + \nu_{jtv}. && (7) \end{aligned}$$

The main concern with estimation of equation (6) is that the error term ξ_{jtv} measures the

[20] We use a Laplace correction to adjust market shares if a source is available but not purchased by any household in our survey sample. This correction is needed because the model will always predict a strictly positive, though small, share for a given source, while exact zero shares are observed in finite samples. For a sample of size n, this correction replaces observed market shares s_j with $\tilde{s}_j = (ns_j + 1)/(n + J + 1)$, which has the effect of giving small, positive shares to any source with a precise zero share, while slightly deflating the shares of other sources. Since we observe availability on the supply side for the grid, microgrid and diesel, separately from whether any household in our sample used a given source, we do not apply this correction if a source was not available in a village. Instead, we remove that choice from the choice set for that village.

unobserved quality of a source, inferred from market shares. If a source is very good in a particular village, for example a diesel operator allows higher loads, then the price of that source may endogenously be set higher, implying $\mathbb{E}[\tilde{\xi}_{jtv}|x_{jtvk}] \neq 0$. We estimate (6) by two-stage least squares, using source-by-wave fixed effects $\overline{\xi}_{jt}$. The first stage (7) uses the experimental treatment assignments, interacted with a dummy for the timing of the endline survey, when the experiment was ongoing, as instrumental variables. The treatment is randomly assigned and so unrelated to village-level source quality. We also know, from Section 3, that the experiment did vary the price of microgrids and so will provide a first stage.

We are also concerned that the hours of supply on the grid may be endogenous to demand. To account for that, in some specifications we also instrument the hours in a village (both on- and off-peak) by a predicted supply using nearby villages. The logic of this leave-one-out estimator is that supply in a given village may be affected by supply in those villages nearby, for instance, due to common rationing rules if they are served by the same substation. This type of supply-side instrument is common in discrete choice demand estimation (Nevo, 2000). In our setting, a supply instrument based on nearby villages is sensible, because the structure of the distribution grid does physically link the supply decisions within a region. The exclusion restriction is that supply of electricity in nearby villages is not correlated to the determinants of demand in a given village. An example where this restriction would be violated is if there are common unobserved demand shocks across nearby villages, conditional on our rich set of household observables. The detailed construction of the supply instrument is presented in Appendix b.

The fitted residuals in the regression (6) estimate the unobserved component of mean utility:

$$\widehat{\xi}_{jtv} = \widehat{\overline{\xi}}_{jt} + \widehat{\tilde{\xi}}_{jtv} = \widehat{\delta}_{jtv} - x'_{jtv}\widehat{\overline{\beta}}.$$

These estimates allow us to observe how the unobserved qualities of electricity sources vary across sources, villages and time.

Counterfactual surplus. With the parameters of the demand model we can calculate household choices and surplus under counterfactuals that vary the availability and characteristics of electricity sources. The aggregate market share of electricity source j is the average household-level choice probability for that source

$$\widehat{s}_{jt} = \frac{1}{N}\sum_{i=1}^{N} \frac{e^{(\widehat{\delta}_{jtv}+z'_{it}\widehat{\gamma}_j)/(1-\widehat{\sigma}_g)}}{e^{\widehat{\sigma}_g \widehat{IV}_{igt}} \sum_{k=1}^{G} e^{(1-\widehat{\sigma}_k)\widehat{IV}_{ikt}}}, \qquad \text{where } \widehat{IV}_{igt} = \ln \sum_{j\in\mathcal{J}_g} e^{(\widehat{\delta}_{jtv}+z'_{it}\widehat{\gamma}_j)/(1-\widehat{\sigma}_g)}.$$

The expected household-level indirect utility from a choice set $\mathcal{J}$ is the log of the sum over nests of a term dependent on nest inclusive value

$$\widehat{\mathbb{E}}\left[\max_j U_{ijtv} \mid \mathcal{J}\right] = \ln \sum_g e^{(1-\widehat{\sigma}_g)\widehat{IV}_{igt}}.$$

We run counterfactuals by considering a restricted set of choices $\mathcal{J}'$ or by using the estimated coefficients to calculate new $\hat{\delta}_{vtj}$ if the characteristics of sources changed. average The willingness-to-pay for a scenario that alters the choice set is

$$\widehat{WTP} = -\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{\mathbb{E}}\left[\max_j U_{ijtv} \mid \mathcal{J}'\right] - \widehat{\mathbb{E}}\left[\max_j U_{ijtv} \mid \mathcal{J}\right]\right) \Big/ \widehat{\widehat{\beta}}_{price}.$$

Predicted market shares and the willingness-to-pay will be the main objects of interest in our counterfactuals.

c Results

This section reports estimates of household demand for electricity sources. We then use these estimates to run counterfactual simulations to value changes in the technology, availability, and pricing of various sources of electricity.

The full demand model has 1033 parameters: 1000 technology-by-village-by-survey mean indirect utility parameters backed out from the first-stage demand model, 29 parameters governing household heterogeneity, 3 parameters on the average effects of source characteristics and a parameter governing correlation of the source-specific utility shocks. We therefore report only select parameters to give a sense of how the model represents household electricity choices. First, we describe the linear estimates of the average effects of source characteristics. Second, we present estimates from the non-linear estimation of how household characteristics affect their choices. Third, we present distributions of source quality to characterize quality changes over time.

Mean effect of source characteristics. Table 4 reports estimates of the linear part of the demand model, obtained by regressing the mean household indirect utility, recovered from the first stage, on source characteristics. Column 1 estimates the linear part of the model by OLS and column 2 instruments for source price using the experimental variation in microgrid prices. Column 3 instruments for price and also for hours of supply, using the imputed hours of supply based on the supply to nearby villages.

The main finding from the linear part is that price has a large, negative effect on mean household indirect utility (column 3). The estimated coefficient associated with a INR 100 price increase is -2.08 (standard error 0.74). To give a scale to this number, the average probability of choosing the grid is 24%, and the model estimates imply that a INR 10 increase in the grid price (17% of the mean price of INR 59) decreases grid market share by 2.9 pp (12% of the average share). The elasticity of grid market share with respect to price is therefore -0.71. We interpret this as a big change in price; INR 10 is enough money to buy two cups of tea or three bananas, but raising the grid price by this amount in a month cuts market share by a noticeable 2.9 pp. Below, e discuss further the elasticities implied by the model estimates.

The experimental variation in subsidy level is critical to identifying the household price response. In an analogous ordinary least squares specification, we find a small, negative and insignificant effect of price on mean indirect utility (column 1). The difference between the OLS and IV estimates of the price coefficient is consistent with either (a) endogeneity of price, wherein higher prices are set in villages with higher-quality products, making the response to price appear inelastic or (b) measurement error in prices, which would attenuate the estimated price coefficient towards zero from below. The experimental instrument has a strong first stage despite the fact that the price variation only applies to one electricity source (column 4). As expected, being in the normal (unsubsidized) price group raises price, whereas being in the subsidized price group lowers price.

Returning to Table 4, we also estimate the effect of hours of supply during the peak hours of five to ten in the evening and during off-peak hours (all other hours) on mean utilities. In the IV specification (column 2), we find a positive but statistically insignificant effect of peak hours of supply and a smaller, negative coefficient for off-peak hours. The estimate of the value of peak hours is not precise, but agrees with the idea that agricultural households mainly value light in the evening hours. In the column 3 specification, we additionally instrument for hours of supply using imputed hours of supply based on supply to nearby villages. We find that the coefficient on price is unchanged and the coefficient on peak hours is positive but still statistically indifferent from zero. The point estimate is somewhat larger than the estimate without instrumenting for hours, from column 2, but we can not reject that the value of peak hours is the same in the two specifications. We proceed with the column 3 estimates, instrumenting for both price and hours, as our main specification for counterfactuals, on the grounds that supply may be rationed in part based on village latent demand, which argues for the instrumental variables approach on *a priori* grounds. We report results from the column 2 specification as a robustness check (CITE APPENDIX TABLE).

Heterogeneity in demand across households. Table 6 shows the estimated effects of household characteristics on choice probabilities in the demand model. The choice probabilities are derived from the estimated coefficients of the demand model, reported in Table 4. The effects of household characteristics on choice probabilities are non-linear; we evaluate these effects for a poor household, which we define as a household of two adults with a one-room house, without a solid roof or walls, that does not own agricultural land. (The full profile of a poor household's characteristics is in Appendix Table D6.) The table shows how the household's probability of choosing each electricity source (across columns) varies with a change in characteristics, either from zero to one (for discrete variables) or of one standard deviation (for continuous variables). Similar tables for median and rich households are presented in Appendix Tables D7 and D8.

The main finding of the table is that richer households, by any measure, have stronger preferences for grid electricity over all other sources. For example, our representative poor household has a baseline 21 percent probability of choosing grid electricity. If the household had a solid roof, the probability of choosing grid electricity would increase by 11 percentage points (standard error 2.5 pp). Similarly, increases in the number of household adults, household income, land holdings, literacy, house quality or the number of household rooms all have positive, economically meaningful and statistically significant effects on the household probability of choosing grid electricity, and all also reduce the probability a household chooses no electricity (the outside option). Some household characteristics also increase household choice probabilities for other inside goods; for example, households with higher incomes are more likely to choose solar microgrids. The effects of household characteristics on demand for the other inside goods, however, are much less pronounced than on demand for the grid. Table 2 offers a natural interpretation of this finding: grid electricity offers higher load, and many more households on the grid can run a fan or a television. Richer households want the energy services these devices bring.

Unobserved source quality. The demand model allows flexibly for changes in ξ_{jvt}, the unobserved mean utility of electricity across villages and time. We call this quality for short. Figure 6 summarizes these source-specific qualities by plotting a histogram for each source: each row is one source and each column is one survey wave. Within each source and wave, the histogram shows the distribution of quality across villages.

The figure shows how the landscape of electrification in Bihar has shifted, with the grid and own solar systems gaining market shares in a relatively short period of time, while other technologies have stagnated. The distribution of diesel generator quality, for example, is about the same in all three survey waves (though there is some truncation at the bottom, due to exits). Our microgrid partner, HPS, did not offer its product in many villages at baseline (which factored into our experimental design). Moreover, it did not change its product between our endline and follow-up surveys, which is apparent in the figure, as the distribution of inferred qualities is similar in the endline and follow-up (row 3, again, with some truncation below). Contrast the stagnation of diesel and microgrids with own solar systems, which shifted up in quality in each survey wave. These improvements could be due to improvements in technical factors such as battery capacity and load, which we do not model directly, or to a broader reach of marketing and distribution of these systems. Finally, we see large improvements also in the quality of the grid, especially between the endline and follow-up survey waves. These improvements show the results of a government drive to increase household connections, which may have increased access and therefore the estimated quality of the grid. There is a remarkable concordance between our prior understanding of changes in quality for each technology in the market and the qualities inferred from the demand model (Figure 6).

Implied elasticities. Table 5 presents the estimated price-elasticities for each source implied by our model.[21] The demand for grid electricity is estimated to be less elastic, at -0.74, than for the other sources of electricity. Own solar and microgrid solar electricity have own price elasticities of -3.48 and -2.34, respectively. Some consumers are tethered to grid electricity and

[21] These are arc-elasticities calculated using a 10% price change for each respective source with respect to its endline average price.

would absorb price increases. A possible explanation is that grid is the only source capable of generating enough power to support large appliances like televisions and fans, which are widely used by richer households.

The increases in electrification over the period of study were therefore due in part to solar innovations and improvements in quality, in part to falling prices for solar systems and in part to a rapid expansion in the availability and quality of grid electricity. We now use the model to break down the contribution of these factors to household surplus.

d Modeling choices

Our model casts household electricity demand as a static differentiated choice problem. Here we discuss several assumptions that this framework makes.

Static model. We use a static model instead of a dynamic model, where households hold sources as assets, or condition future choices on past decisions. We took this route for two main reasons. First, in our context, three of the four sources we study are paid on a monthly basis (own solar being the exception), and so households do not have any asset value from holding these sources. Second, empirically, it does not appear that households are tied to sources they used in the past. We see total disadoption of diesel, and adoption and then disadoption of microgrids, within our study and massive changes in shares from one year to the next. These aggregate movements suggest that households do not behave like a connection to a source is a sunk cost. Our model certainly does allow that there are unobserved adoption or connection costs, via the quality terms.

Substitutes. The structure of our model assumes that sources are substitutes and that households cannot choose bundles of sources. In some settings, for example in cities, households may have diesel generators or solar power to provide power during grid outages, making the technologies complementary. We do not see much of this in our sample, perhaps because households are too poor. At the time of our endline survey, which is used as a point of departure for counterfactuals, only 1.3% held multiple sources (Appendix ADD TABLE ON MULTIPLE SOURCES). For these few cases, we set a priority order where households are assumed to have chosen the grid if the grid is a part of any bundle.

Nested logit. We use a nested logit model instead of a random coefficients (mixed) logit model. There are three reasons for this choice. First, we have especially rich observable household data that allow complex patterns of substitution without random coefficients. Mixed logit models are essential to admit richer patterns of substitution when working with aggregate data and large numbers of product choices (for example, observing one car market with hundreds of models). Using micro-level moments in mixed logit models can help identify model parameters and, with a rich model specification, may be necessary for reliable identification (Berry, Levinsohn and Pakes, 2004). In our setting, we have household-level panel data with unusually rich observable household characteristics, which we show have large effects on demand, and a small number of product choices. Therefore, the aggregate patterns of substitution in the model will not be tied to simple patterns like the independence of irrelevant alternatives, even within nests, because individual households make their own decisions. Second, we find that introducing a small amount of unobservable correlation in tastes, via the nested logit assumption, has negligible effects on the estimates, which suggests a low value, in our data, to specifying a model with random coefficients on additional characteristics.[22] Third, the nested logit model can be estimated efficiently by maximum likelihood, without simulation.[23]

5 The Value of Electrification

The transformation of Bihar's electricity landscape happened on several dimensions at once. The demand model we have estimated now allows us to break down the household surplus from the different changes that Bihar went through, and from counterfactual policy changes that may be expected to increase access or surplus for the poor.

We specify counterfactual scenarios to address three broad questions. First, how much have households benefited from innovation in off-grid solar? Second, what has been the value of government investments to expand grid access? Third, how would further changes in electricity policy—towards access, theft, pricing and quality—benefit the poor?

The third question is acutely policy relevant, because the *status quo* electricity policy in Bihar, as in many other developing economies, is somewhat of a puzzle (Burgess et al., 2019).

[22] Appendix Table D9 shows that the coefficients on observable characteristics and the fit of the model barely change at all when varying the nesting structure, or using a multinomial logit model with no nests at all. Nested logit is a simple case of a mixed logit model where the random coefficients are on group-specific dummy variables (Berry, 1994; Cardell, 1997). The fact that this marginal enrichment of the error structure has no effect on our results suggests a low value to allowing random coefficients on other characteristics.

[23] In principle, one could also estimate a mixed logit model using simulated maximum likelihood, but this approach may be severely biased by simulation error and so is not used in practice (Berry, Levinsohn and Pakes, 2004).

Governments invest large amounts of capital to extend the grid to rural areas but then offer abysmal quality service, rationing the poor customers they sought to reach. Pricing power below cost, and tolerating theft mean the government loses money on electricity supply, and does not have an incentive to improve quality. Our model allows us to study how changes in grid policy would affect household surplus in equilibrium, given the choices that households would make in response to new policies.

a Innovation in solar power

The first set of counterfactuals consider the value of innovation in solar power. The demand model estimates showed that household solar demand is highly elastic. Here we quantify what that elasticity means for households benefits from solar power.

To give a sense of the patterns of substitution between electricity sources, over a range of prices, Figure 7 shows how the market shares of all sources respond to changes in the price of solar. The characteristics and availability of sources are held constant at endline survey levels. The price of solar microgrids, on the horizontal axis, ranges from INR 70 per month, up through the range of our experimental treatments, to a choke-price of INR 300 per month. In the construction of this figure, we vary own solar prices proportionally with microgrid prices, since these sources have similar cost structures. The vertical axis shows market shares for each source technology as solar prices vary.

There are two main results from the figure. First, echoing the elastic reduced-form demand curve for microgrids, we see that microgrid demand is only a few percentage points at INR 200, and that the sum of microgrid and own solar demand together is only a few percentage points by INR 300. Off-grid solar power was not economically viable for this population, therefore, until our study period. Second, as prices rise, households substitute from solar power to grid electricity (blue dashed line), but mostly to no electricity at all (yellow solid line). At higher prices of solar, above INR 200, most households who have grid electricity in their village, and could switch, have switched to the grid, so the grid market share is flat above this level. As the solar price rises further households switch to the outside option of no electricity. Solar serves as a technological stop-gap between the grid and kerosene.

We can use the demand system to recover the value of solar innovation for the poor. We consider the introduction of off-grid solar systems from nothing, essentially the status quo circa 2013, to projected levels of cost in 2022, which are about one third below the subsidized price in our experiment (Feldman, Margolis and Denholm, 2016; Howell et al., 2016).[24] From Figure 7, we can see that bringing the price down from the choke price to the projected levels, where the lines stop at the left side, cuts the share of households with no source of electricity (i.e., increase electrification rates, from any source) by about 35 percentage points.

Figure 8, panel 8A presents the results on surplus due to solar innovation. Each panel of Figure 8 shows a related set of counterfactual scenarios. Within each panel, a cluster of three bars represents outcomes in that scenario: two bars giving the market shares of grid (blue) and solar (own solar and microgrid together, green), measured against the left axis, and one bar giving the total household surplus from electricity sources for that scenario (black), against the right axis. The left cluster in Figure 8 panel 8A, for example, shows that the value of the status quo choice set at the time of our endline survey was about USD 32 per household per year. Unless otherwise noted, in counterfactual scenarios, we hold the characteristics of households and the availability and characteristics sources at endline survey (2016) levels.

Solar has considerable value to poor households. If solar were removed altogether (panel 8A, middle cluster of bars), household surplus from electrification would fall about 40%, from USD 32 to USD 20 per year, though about 5% of the households displaced from solar would connect to the grid. Conversely, if solar prices fall to projected 2022 levels (right cluster), household surplus from solar would rise to USD 38 per household per annum. Solar systems therefore increase household surplus from electricity connections by 90% ($= 100 \times (38 - 20)/20$). The average monthly income in our sample is INR 7576 and the median is INR 6000. Therefore the value of solar power is 1.5% of median household income ($= 100 \times \text{USD}\,18/(12 \times \text{INR}\,6000/60)$ at INR 60 = USD 1). As a point of comparison, we estimate sample households spend XX% of median household income on all sources of energy.

CC: ARE WE USING INR 60 = USD 1 THROUGHOUT?

CC: CALCULATE TOTAL ENERGY SPEND INCLUDING COOKING AND LIGHTING. IMPUTE COSTS FOR COOKING FUEL USING FUEL GATHERING TIME

[24] For solar PV, we assume a 55% reduction in cost (Feldman, Margolis and Denholm, 2016). For batteries, we assume a 75% reduction in cost, in accord with the US Department of Energy's 2022 goal (Howell et al., 2016). Since panel and batteries only make up a part of the system, these changes imply a reduction in total upfront cost of 34%, to USD 1.12, or 33% cheaper than our subsidy treatment (See Appendix Figure E2 for a breakdown of costs). We apply the same proportional reduction in cost to own solar, assuming that the 55% capital component of total upfront cost observed for microgrid applies to own solar as well. This is conservative because the HPS product involves monthly recharge costs that do not apply to the own solar product, so the cost of own solar, being made up mostly of capital, may in fact fall more than we forecast.

Had the grid been absent, the value of solar would have been higher still. If solar cost falls to 2022 levels, but the grid had not connected to our sample villages (panel 8A, right cluster of bars), then solar market share would have risen to XX%. Surplus falls from the removal of the grid, to USD XX per year, but falls *less* than it would have if solar had not been present to pick up the slack (Figure 8, panel 8A, second cluster of bars). The value of solar is XX% higher if the grid is absent. The importance of grid-solar substitution may explain why solar take-up and solar businesses appear to be thriving in sub-Saharan Africa, where the grid is much sparser than in India.

There is another, ancillary beneficiary from off-grid solar: the government. Table 7 presents counterfactual results on market shares, household surplus and producer surplus. Each row is a counterfactual scenario. The columns describe: market shares for each source of electricity (columns 1 to 5); mean consumer surplus for households below the poverty line (6), above the poverty line (7) and all consumers (8); producer surplus (9) and total surplus (10).[25] In our sample 76% of consumers are BPL. BPL consumers are modestly but significantly poorer on all the household characteristics that enter the demand model (Appendix Table C5). Since the model allows for heterogeneity in demand by household characteristics, surplus for BPL and APL consumers may differ, although we do not condition demand directly on BPL status.

Producer surplus is the absolute surplus we estimate for the grid only. It captures profits or losses that accrue to the state from supplying grid electricity and is typically negative, due to high rates of theft and non-payment. Producer surplus for the grid can be taken as capturing producer surplus from the whole market, if we assume that the other sources are competitively supplied; this is probably accurate for own solar but not for diesel (which, in any case, has a small share at endline). All surplus measures are in units of per household per year.

Table 7, Panel A shows that the model, by design, fits endline market shares exactly, which is by design since the source-by-village-by-wave mean utilities come from matching model-implied shares to empirical shares. In the data, 57% of households have no electricity access. The grid is the most popular source of electricity, with a 24% share, but the two types of solar are not far behind, with a combined 17% share. Consumers have a mean surplus of INR 1939 (column 8, USD 32) per year and the state distribution company a surplus of

[25] Below Poverty Line (BPL) is the official classification of poverty in India and entitles households to in-kind food rations. BPL status is determined by DESCRIPTION OF HOW BPL IS JUDGED IN BIHAR.

negative INR 497 (column 9, USD 8).

Now we return to the result on how the government benefits from off-grid solar. In the status quo at endline, producer surplus is INR -497 per household per year. Panel B presents the various counterfactuals on solar power. If solar power disappeared, producer surplus would fall to INR -612; if solar power fell in cost, it would rise to INR -441. Thus the advent of solar power from nothing to 2022 levels, which soaks up loss-making consumers totaling 8 percentage points of the population from the grid, reduces the government's losses by 28% ($= 100 \times (612 - 441)/612$).

We need to stick with one currency or the other. Charts are in USD and tables in INR. My vote would be stay with INR and give references to USD.

b Improving grid access

Our experiment is based in a setting where the grid is deficient: it is offered only in some villages and even conditional on availability, the average supply is merely 11 hours per day. The effects of solar on electrification rates would likely have been different if the grid was everywhere (which would give households better substitutes) or if the grid was 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 removing grid electricity from the choice set or by extending it to all villages. The counterfactual results are presented in Table 7, Panel C and shown graphically in Figure 8B. Improvements to the availability and quality of the grid would increase electrification, with an effect similar in size to that of further innovation in off-grid solar. By the time of our endline survey, the grid had reached 57% of sample villages. If the grid were to be removed from all villages, the share of households without electricity from any source would rise from 57% to 63%, and household consumer surplus from all sources would fall by 43% (Figure 8B, Panel B, third cluster of bars; see also Table 7, Panel C, row 2). If the grid were to be extended to all villages, it would increase electrification by 13 pp and household surplus from all electricity sources by 26%, relative to the status quo, or 120%, relative to no grid anywhere (the rightmost cluster of bars in Figure 8B, Panel B; Table 7, Panel C, row 3). Even after this grid extension, we estimate that 44% of households would remain without any source of electricity. The finding of low rates of household level electrification even after universal village level electrification shows why progress on connecting rural households in poor countries has been slow.

One reason that grid adoption may be low is that quality is poor. We simulate improvements in grid supply that increase the duration of power available by two hours per day (up to five hours, the number of peak hours per day, if a two hour increase would exceed five peak hours in total). This allows us to compare the intensive and extensive margin of policy changes. If the grid were to offer two more hours of power during the peak period, we would see 5 pp more households on the grid (Table 7, Panel C, row 4). CHECK WHY MORE HOUSEHOLDS WITH SOLAR IN THIS SCENARIO: DOES NOT MAKE SENSE UNLESS SOMETHING ELSE IS CHANGING IN THE COUNTERFACTUAL–SOLAR MARKET SHARES SHOULD COME DOWN. The poor quality of the power grid therefore has a meaningful effect on whether households get an electricity connection, but even full supply on peak hours would leave roughly half of households choosing not to purchase any source of electricity.

c Rationalizing grid policy

Electricity in Bihar is heavily subsidized and the state tolerates a high level of theft, which further lowers effective prices. Here we use our demand model to understand why the government chooses this particular low price, low quality bundle of grid energy services.

First consider pricing. Low rates of payment, in our model, are measured by a low price for grid electricity (See Section 2 b). We counterfactually raise the price of grid electricity from INR 73 per month to INR 140, which we calculate would be sufficient to cover the variable costs of supply. Raising the price of the grid to cover the variable cost of supply would devastate grid market share (Figure 8B, Panel C, middle cluster of bars): the number of households on-grid in this scenario falls from 24% to 5%. The price increase cuts household surplus from electricity from INR 1939 (USD 32, leftmost cluster of bars) to INR 1299 (USD 21), which is 80% of the drop that would occur from removing the grid altogether. That is, a grid priced at cost might as well not exist for this population. This large swing in market share may seem extreme, but is consistent with our experimental estimates, in particular the high price-sensitivity for solar around the price (INR 100 per month) of competing options like diesel power (Figure 5). The total solar market share doubles, to about 30 percentage points, as grid leavers adopt off-grid solar. The government does much better: producer surplus rises from INR -497 to -52, nearly break-even. WHY NOT ZERO IF PRICED AT COST?

A less drastic reform would try to move from the present low price, low quality bundle to a higher price, higher quality bundle, to compensate households for their additional payments with better energy services. Many policy observers recommend reforms of this kind CITE FROM WB, IMF OR OTHER PARTY. We use the model to consider a budget neutral "grand bargain": the government increases supply during peak hours and pays for that increase by raising prices. We calculate that a price increase to INR 90 per month would be sufficient to pay for the increase in supply. Figure 8B, Panel C shows the result in the bars at right, with further detail in Table 7, Panel D.

The grand bargain scenario yields slightly *lower* total surplus than the status quo (INR 1363 down from INR 1442, Table 7, Panel D, second row). The decline is greater for households below the poverty line (column 6, INR 100 per household) than above (column 7, INR 16), despite that APL consumers get higher surplus from electricity overall. The share of households with no electricity falls slightly, as some households are attracted to the greater peak supply on the grid (column 5), even as the increase in price pushes other households off the grid towards solar (column 3 and 4). The interpretation that the grand bargain roughly breaks even depends on the model specification we use to a greater extent than do the other counterfactual findings.[26] Yet, in no specification do we find that the government can offer a bundle of electricity services that clearly dominates the status quo.

6 Conclusion

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Electricity markets in the poorest parts of the world are undergoing radical changes. On the one hand, darkness is still a pervasive problem — roughly a billion households, mainly in South Asia and Africa, remain without any access to electricity. On the other hand, consumers enjoy a growing number of choices on where they can source electricity from – technological innovations are making off-grid solar a viable alternative to the grid and governments are prioritizing extending the grid to poorer, rural areas. The main contribution of this paper is

[26] We estimate the value of price to consumers using our experiment, but do not have as strong an instrument for hours of supply. Because our estimate of the value of peak supply is imprecise, the conclusion depends on the exact specification of the demand system. For example, if we were to instrument for price but not for hours, in the second, linear stage of the demand model, then the grand bargain would decrease total surplus, due to lower household valuation in that specification. Hence, the finding that the grand bargain breaks even in surplus terms is perhaps slightly optimistic.

to create a demand system founded upon experimental variation in solar prices that allows us to assess household willingness-to-pay for different sources of electricity. Through our demand model, we can assess how households of different types value different sources of electricity, which in turn allows us to investigate whether the darkness problem in the rural areas of developing countries reflects a failure in expanding access to electricity or an unwillingness by poor, rural households to pay for electricity relative to other consumption goods.

Access to electricity from the grid is taken for granted in developed countries but vast swathes of communities in the developing world either lack access to it altogether, or receive rationed, intermittent supply. In rural Bihar, one of the poorest parts of the world, our data collection efforts reveal that this scarcity of formal grid has engendered a rich, dynamic parallel market for alternative sources of electricity. Our surveys, conducted in 100 villages in India's poorest state, uncover innovations in off-grid solar technologies and government-led grid expansions which imply that households face a growing choice set on where to source electricity from. Where there is sufficient demand, markets for diesel generators have also popped up. Still others choose to buy their own solar panels but at a substantial cost. New technologies such as microgrid solar have also been introduced to this competitive market. Our study was well timed to capture this period of dramatic change in the electricity market. This region had epitomised the problem of darkness enveloping the developing world — at baseline, just 27% of households within our sample villages had access to electricity and electrification rates were below those in sub-Saharan Africa. Just four years later that number had jumped to 64%, with the expansion of the grid and the spread of own solar playing key roles.

In this fast evolving setting, we carried out an RCT varying the price and availability of a new off-grid technology - microgrid solar. In partnership with HPS, we randomly assigned the availability and price of microgrids across 100 villages and monitored the evolution of demand for this electricity source and its competitors via an innovative survey instrument over three waves. The obvious fruit of our experiment is a demand curve for microgrids. However, this paper's key innovation arguably lies in our subsequent combination of the experimental price variation created by the RCT with a rich dataset comprising both demand- and supply-side information. This enabled us to estimate a multinomial demand model that captures the electricity market as a whole, by quantifying market shares and household willingness-to-pay for the main sources of electricity in rural Bihar (grid, diesel, own solar, and microgrid solar).

We then employed our model to construct counterfactuals, yielding valuable out-of-sample predictions for how the market is likely to respond to future innovations in solar technologies and potential changes in the functioning of the electricity distribution system.

Our reduced-form estimates point to a high price-sensitivity by consumers for microgrids, with demand dropping to near 0 at unsubsidised prices. Moreover, evidence suggests demand shifted inward over the course of the experiment, with only 7% of households paying at the subsidised price at endline. This is in-line with the strong and increasing competition observed in electricity markets. Despite low take-up, households in subsidised treatment villages in particular were significantly more likely to own light bulbs, use more electricity, purchase more mobile phones and spend less money on charging them. We were largely unable to detect any benefits to household income, children's reading and math test scores or self-reported respiratory problems. Overall, this supports the view that solar microgrids are valuable for certain households but not transformative in the way that some have hoped for.

One of our multinomial demand model's key results is that richer households, by any measure, have stronger preferences for grid electricity relative to other sources. This is likely attributable to the grid's unique ability to support larger appliances such as televisions and fans, which richer households demand. It also substantiates the reduced-form result that households are highly price-elastic — raising the price of the grid by just the cost of two cups of tea is estimated to reduce electrification by 3 pp.

This finding of high-elasticity implies that anticipated innovation in solar technology and small changes in government policy, which in turn affect the characteristics of different electricity sources, may have dramatic effects on the electricity market. These are explored in our counterfactual analysis. We find that further reductions in solar prices would moderately increase its market share, mostly arising from adoption by households that would not have otherwise been electrified. However, when grid is not available, solar market share is limited to 34% and almost two thirds of households would choose to remain in darkness. Because willingness-to-pay for off-grid solar is considerably lower when the grid is available, solar appears to be more of a stop gap – albeit a potentially important one – for households that do not have access to grid electricity or for poor households who cannot afford full-price grid electricity. In this sense, solar power is valuable in large part because the grid is incomplete and dysfunctional.

Another key contribution of this paper is to rationalize India's existing system of simultaneously subsidizing (explicitly through low official prices or implicitly through tolerance for rampant theft via informal connections to the grid) *and* rationing electricity. In particular, our counterfactual analysis predicts that raising prices or cracking down on non-payment would devastate electricity access among the rural poor — households are highly price-elastic and would simply opt to live in darkness. This is at odds with the view that households value electricity and benefit from the extensive, on-going efforts in developing countries to expand access to electricity, via either on- or off-grid mechanisms.

Our demand model suggests an alternative interpretation of enthusiasm for solar power for off-grid, small-scale use in developing countries: the government may want to subsidize off-grid solar for purely cost reasons. Tolerance for theft, as much as being able to serve higher loads, is a large part of the grid's appeal in this setting. Every customer that better solar power takes away from the money-losing grid increases the state's producer surplus by reducing losses. These monetary considerations are large, with solar's entry saving the government a sum of money about equal to what the households that take-up solar pay themselves.

A broader question that our static analysis cannot answer is what is the cost of this dysfunctional electricity supply sector in the longer run. There is some evidence that electrification has large external returns (Lipscomb, Mobarak and Barham, 2013). It is hard to imagine a large business, for example in manufacturing or services, opening in an area with eleven hours of daily electricity supply (Allcott, Collard-Wexler and O'Connell, 2016). The combination of these facts implies that, even if rationing electricity is a statically necessary policy to support electricity access, it may limit rural growth. Moreover, off-grid solar systems cannot replace the scale economies of a well-functioning electricity grid.

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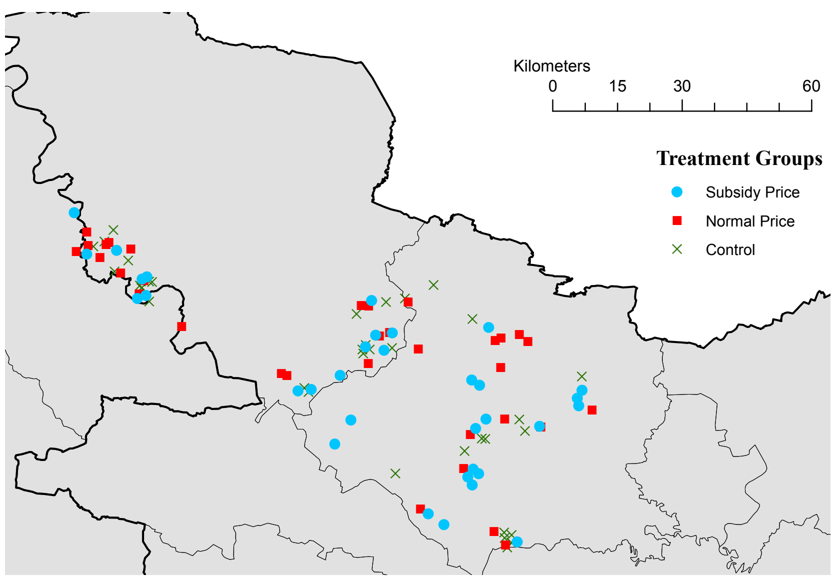
7 Figures

Figure 1: Maps of Study Area

(A) Study districts within the state of Bihar, India

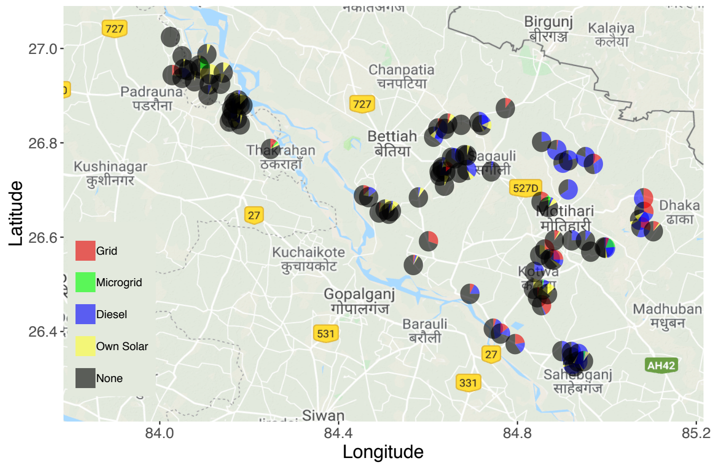
(B) Sample villages within study districts



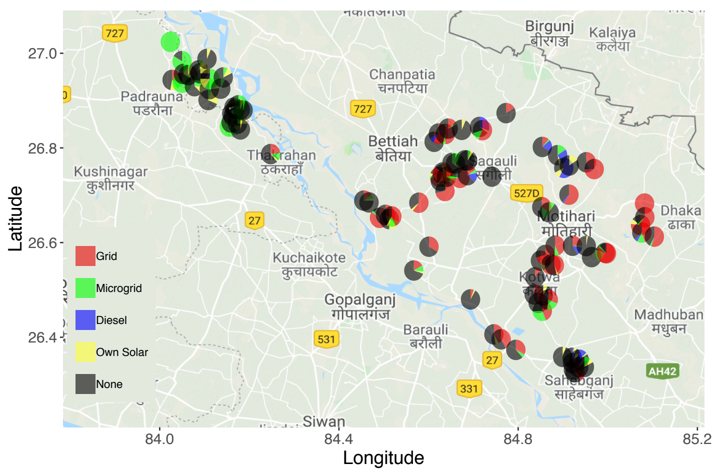
The figure shows the location of the study area. Panel A highlights the two districts of West Champaran and East Champaran in northwestern Bihar state where the study villages are located. Panel B shows, within the two study districts, the locations of sample villages and their treatment assignments. The nearest large towns are Bettiah and Motihari. The river Gandak in the northwest forms the state border with Uttar Pradesh.

Figure 2: Sources of Electricity for Households in Rural Bihar

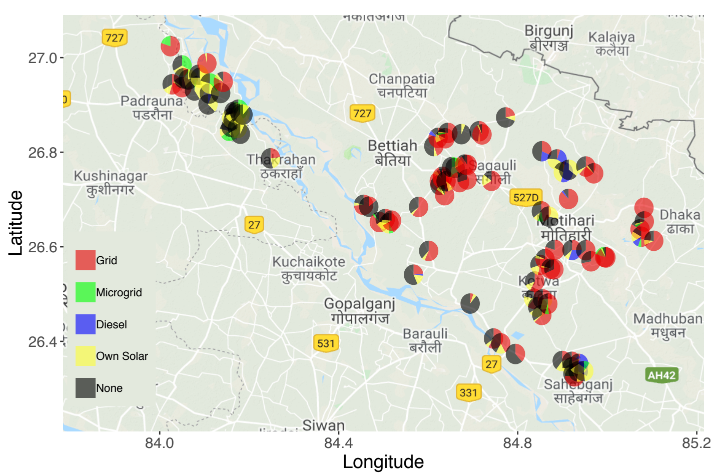
(A) Baseline: Nov-Dec 2013



(B) Endline: May-July 2016

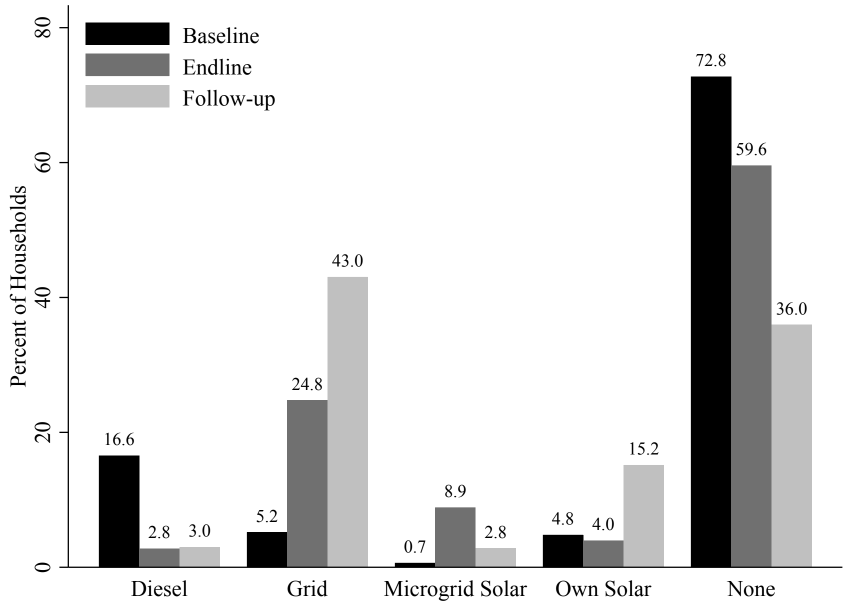


(C) Follow-up: May-June 2017



The figures show the highly dynamic composition of the electricity market in our sample villages across the three survey waves. There is considerable heterogeneity in the availability of grid, diesel, and solar across space and time. In fewer than four full years, the grid electrification rate in our sample rose from 5% to 41%. At the same time, the share of sample households with electricity from diesel generators fell from 17% to 3%, and the share with their own solar systems leaped from 5% to 21%.

Figure 3: Take-Up of Electricity Sources by Survey Wave



The figure shows the take-up of electricity sources across the three different waves of our household survey. Each group of bars shows the market shares of a given electricity source across sample households. Diesel is diesel generators, grid is the state-run electricity grid, microgrid solar is the HPS solar microgrid offered in the experiment, and own solar is individual household-level solar systems. Within each group of bars the market share is shown for each of three survey waves. The survey waves are: baseline (starting November, 2013), endline (starting May, 2016) and follow-up (starting May, 2017).

Figure 4: Market Share of Electricity by Household Income Profiles

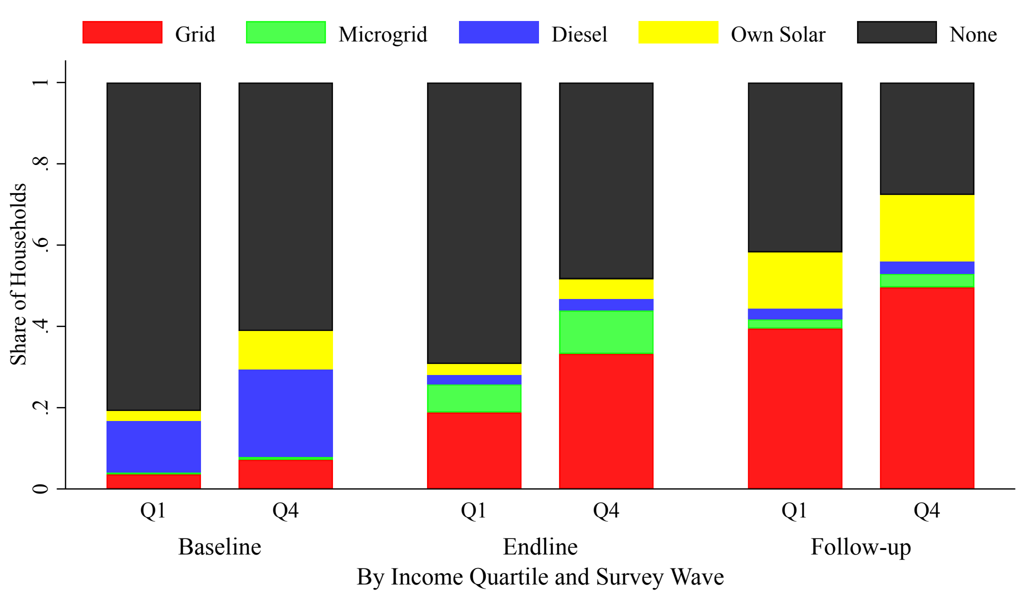
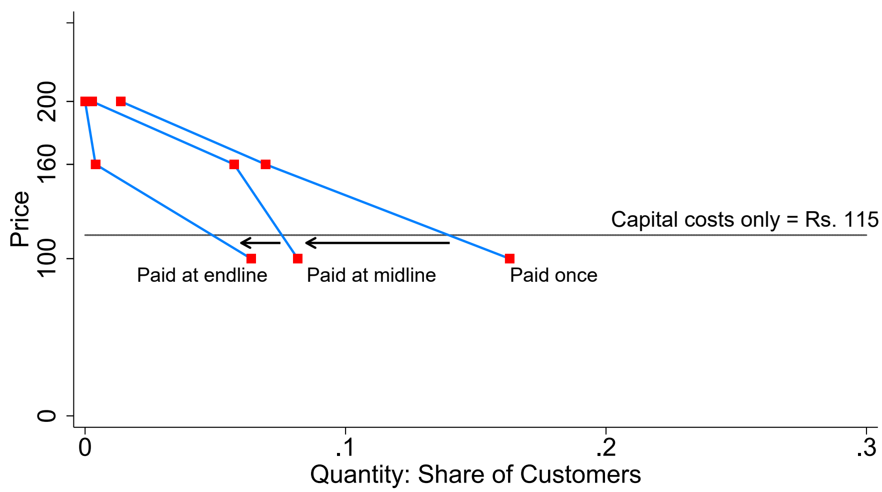
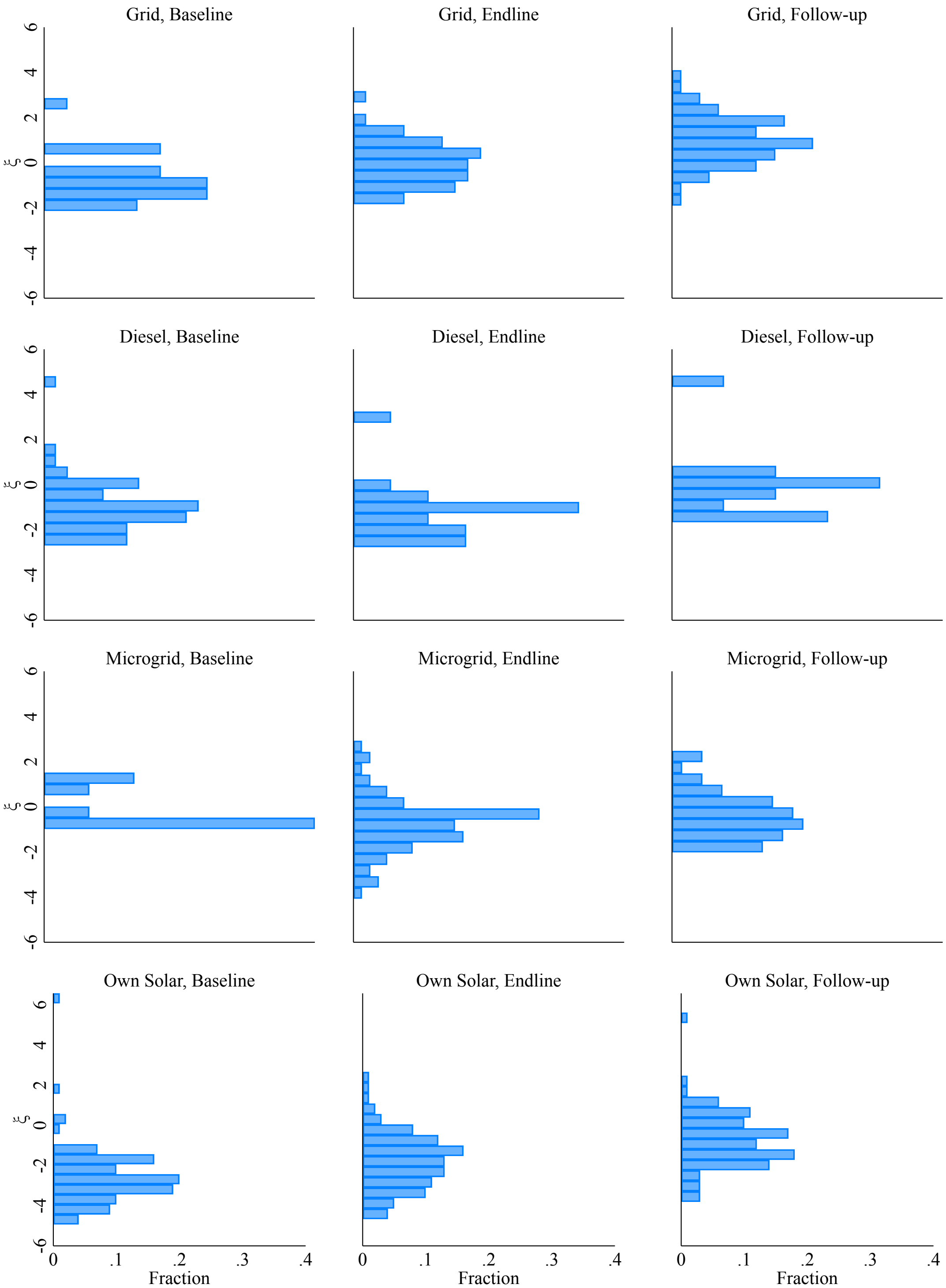


Figure 5: Demand Curve for Microgrid Solar



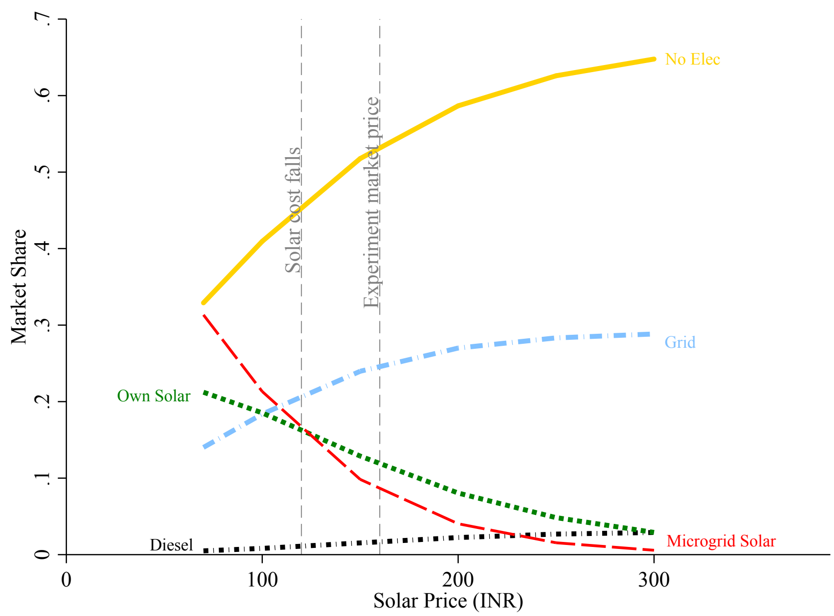
The figure plots the share of sample households that paid for the Husk Power Systems (HPS) solar microgrid at three different times. The horizontal axis is the share of households paying and the vertical axis is the monthly price. Each line on the figure represents the demand for solar microgrids at a different point in time. The outer demand curve is for households who paid at any time during the experiment; the middle curve for households that paid at the midpoint of the experiment (months 16-18); the inner curve is for households that paid during the endline one survey (starting in May, 2016, month 29). At each point in time household demand is shown for three different prices. The horizontal line on the figure is an estimate of the amortized monthly capital costs of the microgrid system per household. This cost does not include costs such as marketing, billing or operations and maintenance.

Figure 6: Distribution of Unobserved Mean Utilities (ξ_{vtj}) by Source and Wave



The figure plots the quality of different electricity sources over time. The four rows are for different electricity sources, from top to bottom: grid electricity, diesel, HPS solar microgrids, and household's own solar systems. The four columns are for different survey waves, from left to right: baseline (starting November, 2013), endline one (starting May, 2016) and endline two (starting May, 2017). Each tiled panel in the figure shows the distribution across villages of source-specific unobserved mean quality ξ_{vtj} for the row source during the column survey wave. The vertical axis is the value of mean unobserved quality, where the outside option is normalized to zero, and the horizontal axis is the density of the historgram. The mean unobserved quality is estimated in the demand model as the residual that fits source market shares given the observed characteristics of each source. The unobserved quality is therefore only recovered, and plotted, for source-village-wave combinations in which a given source was offered (i.e., it is not possible to infer grid quality when the grid is not present in a village).

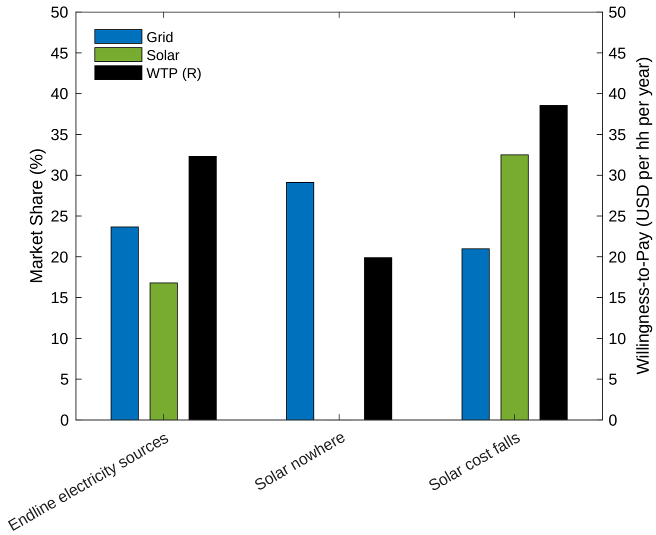
Figure 7: Market Shares under Varying Solar Prices



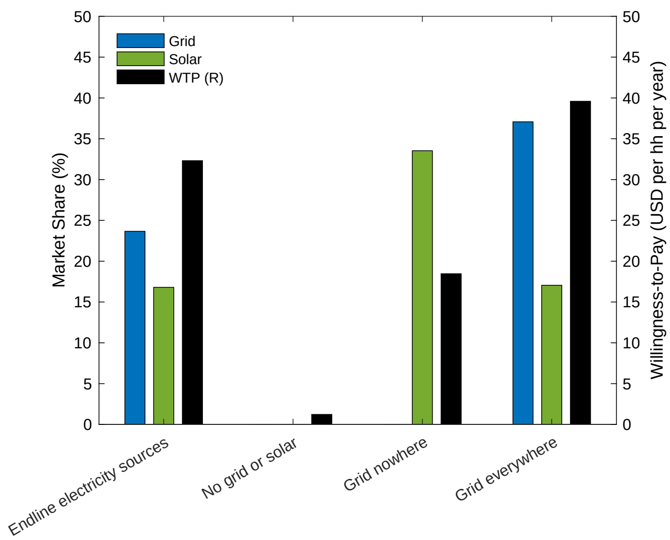
The figure shows demand for all electricity source technologies as the price for solar power varies. Each curve is the predicted market share of an electricity source technology. The horizontal axis gives the price of an HPS solar microgrid. While the horizontal axis shows the price of an HPS solar microgrid only, we vary the price of own solar systems proportionately with the microgrid, on the grounds that capital cost reductions in solar photovoltaic panels or batteries would affect the price of both productions in proportion to their capital share. The microgrid price shown in the figure ranges from INR 70 up to the choke price of INR 300. Household and source characteristics and the availability of all sources are fixed at their endline one (mid-2016) levels.

Figure 8: Counterfactuals

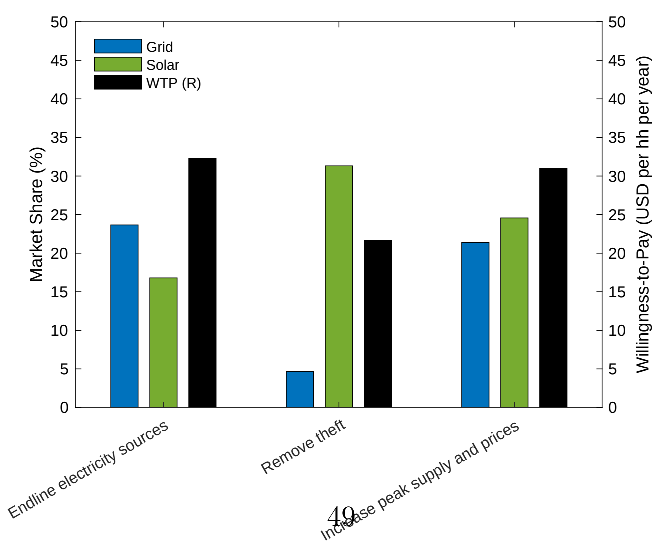
(A) Value of Solar



(B) Value of Grid



(C) Reform grid policy



8 Tables

Table 1: Electrification Context Around the World

	United States (1)	India (2)	Sub-Saharan Africa (3)	Bihar (4)
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

The table places the income and electricity access in the state of Bihar, India, the site of the study (column 4), in the context of other areas of the world (columns 1 through 3). The first row is nominal GDP per capita, the second row is mean electricity consumption per capita, the third row is the electrification rate and the last row is the ratio of mean electricity consumption per capita to mean consumption in the United States. The source of data is (World Bank, 2017).

Table 2: Summary of Electricity Sources, All Panels [NEED CODES]

	Grid (1)	Diesel (2)	Own Solar (3)	Microgrid (4)
Panel A. Baseline				
Monthly price (Rs.)	73.26	98.88	74.43	200
Load (watts)	322	133	151	28
Supply hours	9.74	3.38	7.92	3.14
Source available (percent)	35.3	62.1	100	.65
Panel B. Endline				
Monthly price (Rs.)	59.34	87.50	96.06	164.07
Supply hours	10.01	3.08	5.71	6.16
Source available	58.9	10.1	100	66.4
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
Monthly Income (Rs.)	9222	8547	8760	8493
Panel C. Follow-up				
Monthly price (Rs.)	58.71	88.90	66.08	170
Supply hours	12	3.08	5.7	6.16
Source available	76.3	15.4	100	65.7

The table shows characteristics of the various sources of electricity that constitute the rural electricity market we study. 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 3: Baseline Covariate Balance

	Control (1)	Normal (2)	Subsidy (3)	Diff(N-C) (4)	Diff(S-C) (5)	FTest (6)
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 microgrid 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	

The table reports 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 differences 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0:01$

Table 4: Two-Stage Least Squares Estimates for Demand for Electricity

	OLS (1)	Price IV (2)	Price & Hours IV (3)	Price First Stage (4)
Price (Rs. 100)	-0.19*	-2.08***	-2.07***	
	(0.11)	(0.74)	(0.74)	
Hours of supply on peak	0.20	0.10	0.19	
	(0.21)	(0.21)	(0.27)	
Hours of supply off peak	-0.092*	-0.077*	-0.11*	
	(0.047)	(0.047)	(0.060)	
Normal Price				0.045
				(0.035)
Subsidy Price				-0.14***
				(0.031)
Peak Hours Instrument				-0.032
				(0.044)
Peak Hours Instrument				0.0037
				(0.0091)
ξ_{tj} mean effects	Yes	Yes	Yes	Yes
Observations	1000	1000	1000	1000
fstat				

The table presents 2SLS estimates of our demand system. The dependent variable is mean indirect utility at the market × survey wave level retrived from the non-linear first stage. Peak hours refers to supply of electrricity during the evening (5pm-10pm). The second column presents two-stage least squares estimates where instrument price with the experimentally varied HPS treatment assignment. In the third column we instrument for price and peak, off-peak hours. For grid hours, we use predictions from a random forest model (see appendix for details) as instruments. For off-grid sources, we use the data out instrument matrix. The last column provides first stage regrressions for the specification in column 2. First stage regressions for the specification in column 3 are presented in the appendix Table D11. All regressions control for wave × source mean effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors cluster at the village level in parentheses.

Table 5: Price Elasticity of Electricity Sources

	Price Elasticity
Grid	-0.74
Diesel	-1.34
Own Solar	-3.48
Microgrid Solar	-2.34

The price elasticity for a given technology is calculated by calculating the percent change in its market share induced by a 10% increase in its price above its mean endline price.

Table 6: Impact of Household Characteristics on Choice Probabilities

	Grid	Diesel	Own Solar	Microgrid	None
Number of adults	0.036	0.002	0.001	0.005	-0.045
	(0.009)	(0.006)	(0.001)	(0.004)	(0.008)
Household income	0.016	0.002	0.001	0.014	-0.034
	(0.007)	(0.005)	(0.001)	(0.004)	(0.008)
Household owns land	0.049	-0.023	0.003	0.008	-0.037
	(0.018)	(0.010)	(0.003)	(0.009)	(0.016)
Household head literacy	0.026	0.008	-0.001	0.002	-0.036
	(0.008)	(0.005)	(0.001)	(0.004)	(0.007)
Pukka (solid) house	0.077	-0.004	-0.002	-0.006	-0.065
	(0.023)	(0.013)	(0.003)	(0.008)	(0.019)
Solid roof	0.107	-0.007	0.005	-0.007	-0.098
	(0.025)	(0.013)	(0.003)	(0.007)	(0.018)
Number of rooms	0.026	0.011	0.003	0.003	-0.043
	(0.008)	(0.005)	(0.001)	(0.004)	(0.008)

The table shows the discrete effects of changes in household observable characteristics (in rows) on the probability the household will purchase different electricity sources (in columns). The household characteristics are from our survey. The changes in choice probabilities are calculated with the demand model, for which the estimated coefficients are presented in Appendix Table D11. Each cell entry is the change in choice probability for a poor household from increasing the row characteristics. For discrete household characteristics, the increase is from zero to one. For continuous household characteristics, the increase is of one standard deviation. Appendix Table D6 describes the statistical profile of a poor household and Appendix Table C3 shows the magnitude of changes in household characteristics for each variable. Standard errors are constructed using the delta method.

Table 7: The Value of Electrification under Counterfactual Policies

	Market shares					Surplus (INR per household per year)				
						Consumer				
	Grid (1)	Diesel (2)	Own solar (3)	Microgrid (4)	None (5)	BPL (6)	APL (7)	All (8)	Producer (9)	Total (10)
Panel A: Fit of model										
Data	24	3	7	10	57	-	-	-	-	-
Model	24	3	7	10	57	1849	2208	1939	-497	1442
Panel B: Value of solar innovation										
Solar nowhere	29	3	0	0	68	1087	1513	1193	-612	582
Solar everywhere	23	2	13	10	51	1801	2277	1920	-492	1428
Solar cost falls	21	1	17	16	45	2199	2654	2313	-441	1872
Further solar innovation	17	1	36	8	39	3737	4185	3849	-349	3500
Panel C: Grid Extension										
No grid or solar	0	5	0	0	95	58	120	74	0	74
Grid nowhere	0	3	20	13	63	1039	1312	1108	0	1108
Grid everywhere	39	1	8	9	44	2342	2710	2434	-803	1631
Extra 2 Hours	29	2	12	10	48	2037	2568	2170	-736	1434
Grid everywhere and solar cost falls	34	1	11	14	41	2649	3024	2743	-708	2035
Grid everywhere, increase peak hours, and solar cost falls	45	0	7	12	36	3020	3412	3118	-1115	2004
Panel D: Theft Reductions										
Remove theft by raising grid price	5	3	19	13	61	1217	1543	1299	-52	1247
Increase peak supply and raise prices	21	2	14	11	52	1749	2192	1860	-497	1363

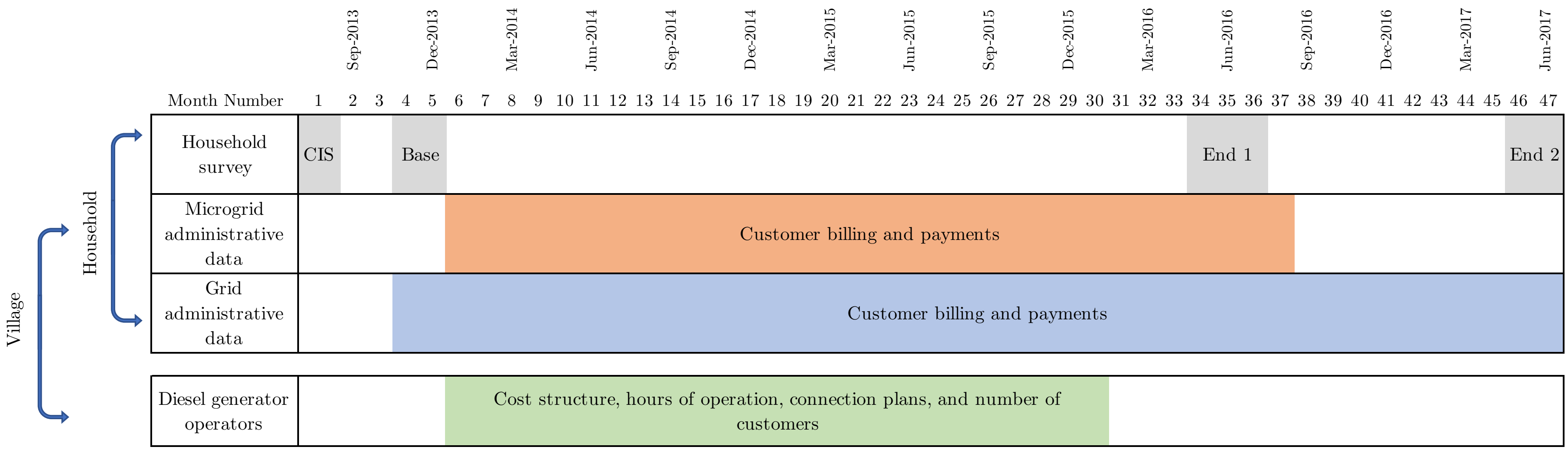
The table presents market shares and surplus under counterfactual changes in the supply side of the electricity market. All counterfactuals are calculated using our demand model estimates. The counterfactual scenarios are laid out in Section **??** of the text and the detailed assumptions behind the counterfactuals are in Appendix Table **??**. In Panel A, we compare the market shares in the data at the time of the endline one survey (mid-2016) to market shares in the model. Panel A, row 2 is the baseline scenario for surplus in the status quo. In Panel B we vary the availability, price, and quality of off-grid solar. In Panel C we vary the availability and quality of the grid. In Panel D we vary the pricing and supply of the grid. Within each panel, we report surplus divided into several categories. Consumer surplus is surplus relative to the outside option of no electricity. We report mean surplus per household per year for households below the poverty line (BPL), above the poverty line (APL) and all households. BPL is the government's official designation of poverty. Producer surplus is the surplus of the grid only. To calculate grid surplus we use the mean consumption of 60 kWh per month in administartive billing data and the power supply cost of INR 3.88 per kWh from the distribution utility's 2014-15 tariff order. At these costs the utility loses money on each customer so producer surplus is negative. The Panel D, row 1 counterfactual has a grid price of INR 140 and the Panel D row 2 counterfactual a grid price of INR 110 per month.

A Appendix: Data

a Sampling and timeline

DESCRIBE EXPERIMENTAL TIMELINE HERE.

Figure A1: Data Collection Timeline



Household survey, microgrid administrative data, and grid administrative data are each at the household-level. We connect these 3 sources together by using unique household identification numbers. Finally, we enrich our dataset by joining in diesel operator data at the village-level. In Aug 2013, we conducted a customer identification survey ("CIS") for the villages in our study, which was subsequently used to assign villages to treatment and control groups and also served as the basis from which we drew our household sample. In each of the household baseline and endline surveys, we collected data that covered demographics (e.g. literacy and number of adults per household), wealth proxies (e.g. income, size and structure of house and ownership of agricultural land), electrification status (e.g. all sources from which the household procured electricity and payments for each source), and quality of electricity sources (e.g. load and daily hours of supply). Moreover, we also recorded ownership of assets such as mobile phones, bulbs, fans and TVs, and tracked select measures of education and health, namely children's reading and math test scores and self-reported respiratory problems. The household follow-up survey was a shorter survey in which we recorded data on demand for and use of different electricity sources. We also collected household consumer IDs in this survey, which facilitated household matching across datasets and allowed us to distinguish formal (i.e. paying) consumers from informal (i.e. non-paying) consumers.

b Construction of instrument for hours of supply

The imputation of missing feeder supply data is done in two steps.

1. If supply data for a village is missing for a given survey wave but some data is available for that village in the $+/-6$ month window, we replace the missing observation with the temporal mean of available data in this time window.

2. If a village has missing data for all months in the $+/-6$ month time window, we use a random forest (RF) algorithm to impute missing hours of supply for that village.

RF has the advantage that it necessarily yields internal predictions and so imputed hours of supply are sensibly bounded. We include the following predictor variables (features) in the RF model: (1) hours of supply of the three nearest villages for which we do have data, (2) division fixed effects, (3) polynomials upto degree 5 of district-demeaned latitude and longitude of each village, and (4) interactions of division fixed effects with each of the demeaned lat-lon polynomials. Hence, all the features that go into the RF model are plausibly exogenous to our demand model. We exclude unelectrified villages (supply for these is replaced zero) from the sample because we don't want to use data of unelectrified villages to impute missing supply data for electrified villages. For instance, there are 56 electrified villages in the endline survey which have non-mising data. This is our master sample for the RF model. We randomly select 80% of this sample (45 obs) as the training sample and the remaining 20% as the testing sample (11 obs). The RF model is fit on the training sample.

Figures ?? and ?? describe our prediction model. The main parameter to tune in a random Forest model is the number of candidate variables to select from at each split. To do this, we start with 2 variables and increase by a step factor of 1.5 until the improvement in out-of-box (OOB) error is less than one percent. As shown in panel A of Figure ??, for the endline data, this yields 6 variables. Figure ?? shows the most relevant variables chosen by the model.

The RMSE of our prediction model is 1.9 hours. We take the predictions from this model and use them to impute missing observations in administrative grid supply data.

In one our second-stage two-stage least squares specifications (Table 4, column 3), we instrument for peak and off-peak hours of supply of electricity, in addition to price. Microgrid, diesel, and own solar have constant supply hours in all villages. For microgrid and diesel, this is 0 for off-peak hours and 5 (maximum) for peak hours. For own solar, it is the global median of the peak and off-peak hours for that source. For grid, supply is observed from administrative log-books at the feeder level, mapped to sample villages. We use our predictions from the above random forest model as the instrument for grid supply.

B Appendix: Impact analysis of solar microgrids

The demand curve reflects household willingness to pay for off-grid solar electricity. This willingness to pay reflects perceived household benefits from having a connection. There may

Table B1: Household Electricity Use Outcomes

	Light Bulb Ownership (=1) (1)	Daily Hours of Electricity Use (2)	Mobile Phone Ownership (3)	Price of Full Charge (Rs.) (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

The table shows regressions of ownership of LED lamps and one mobile charging point and the use of electricity on treatment status. Households in the treatments got and used electricity microgrids and these appliances. The specifications include baseline electricity source indicators, baseline monthly income, and baseline equivalent of outcome variable as controls. Standard errors clustered at the village level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

also be benefits of solar power that are not perceived or valued by the household when choosing whether to buy microgrids. For example, improved lighting can 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 microgrid electricity on a battery of social outcomes. We begin by estimating a reduced-form model of the following specification:

$$y_{ivt} = \alpha + \beta_N NormalPrice_v + \beta_S SubsidizedPrice_v + \mathbf{x}_i'\delta + \epsilon_{itv} \tag{8}$$

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 microgrids at regular and subsidized prices, respectively, and $\mathbf{x}_i$ is a vector of controls from the baseline survey. The outcome variables we examined include measures of electricity access, adult and child respiratory problems, reading and math test scores and household income.

Households in both treatment arms got and used electricity microgrids. The microgrid powered two low-wattage LED lamps and one mobile charging point, which was provided with every connection. Table B1 reports regressions of ownership of various appliances and use of electricity on treatment status. Assignment to a subsidy treatment village increases light bulb ownership by 15 percentage points (standard error 4.7 pp) relative to an ownership rate of 32 percentage points in the control group at baseline (column 1). Subsidy treatment households

Table B2: Household Income, Education and Health Outcomes

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

The table shows the effects of provision of solar microgrids 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 of solar microgrids 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 4 and 5). The predominant source of indoor air-pollution comes from cooking, which is unaffected by the provision of microgrids, and we do not find significant declines in kerosene expenditure (not reported). Effects on reading test scores are positive but imprecisely estimated (columns 2 and 3). 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. Test score results are at the child level. The regressions include baseline electricity source indicators, baseline monthly income, and baseline equivalent of outcome variable controls. Standard errors clustered at the village level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 group at baseline (column 2). The effects of being assigned to a normal price village are smaller but have the same sign and are also statistically significant. Households assigned to a subsidy treatment village are also more likely to own a mobile phone, by 3.4 percentage points relative to an already high control group ownership rate of 88 percentage points (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 of money spent charging one's mobile phone, which makes sense because households without electricity will typically charge their mobile phones at a shop for a higher per-unit cost of energy.

We therefore find that when solar microgrids are made available, households use more electricity, purchase more mobile phones and light bulbs, and spend less money charging phones. As we would expect, these effects are more pronounced when prices are subsidized. With regards to social outcomes such as income, education and health, we find little evidence that the electricity provided by solar microgrids had a large impact (Table B2). MORE HERE ON MEASUREMENT: LARGE BUT NOISY ESTIMATES FOR EDUCATION In summary, while the effects of electrification by solar microgrids were not transformative, households still valued off-grid solar for lighting and other energy services.

C Appendix: Additional results

Table C3: Definition of Household Characteristics and Magnitude of Marginal Change

Characteristic	Definition	Marginal Change
Income	Monthly income	1 SD (INR 6486)
Land	Indicator for agricultural land	0 to 1
Roof	Indicator for solid roof	0 to 1
Pukka	Indicator for pukka house	0 to 1
Rooms	Number of rooms in the house	1 SD (1.32 rooms)
Adults	Adults in the HH	1 SD (1.82 persons)
Literacy	Literacy of household head (1-8)	1 SD (2.04 years)

The table shows the magnitude of the change in household covarates for which the marginal impact on household choice probabilities is estimated in Table D7 and Table D8. Literacy classification: 1 =not literate, 2= Aanganwadi, 3 = literate but below primary, 4 = literate till primary, 5 = literate till middle, 6 = literate till secondary, 7= literate till higher secondary, 8 = graduate and above

Table C4: Summary Statistics of Household Characteristics

	Mean	Median	Q1	Q3	SD	Min	Max
Number of rooms in the house	2.45	2	2	3	1.32	1	11
Indicator for pukka house	0.32	0	0	1	0.47	0	1
Indicator for agricultural land	0.63	1	0	1	0.48	0	1
Indicator for solid roof	0.51	1	0	1	0.50	0	1
Literacy of household head (1-8)	2.48	1	1	4	2.04	1	8
Adults in the HH	3.67	3	2	5	1.83	1	15
Monthly income (INR)	7575.5	6000	4000	8500	6486.2	0	65000.0
Observations	8822						

Table C5: Summary Statistics by BPL Status

	BPL	APL	BPL-APL
Rooms	2.38	2.58	-0.20***
	[1.18]	[1.50]	(0.054)
Pukka house	0.33	0.42	-0.088***
	[0.47]	[0.49]	(0.020)
Agricultural land	0.58	0.66	-0.088***
	[0.49]	[0.47]	(0.021)
Solid roof	0.51	0.58	-0.069***
	[0.50]	[0.49]	(0.021)
Literacy	2.25	3.01	-0.76***
	[1.87]	[2.31]	(0.085)
Income	0.73	0.87	-0.14***
	[0.58]	[0.74]	(0.027)
Number of adults in household	3.76	3.88	-0.12
	[1.83]	[2.02]	(0.080)
Observations	2186	731	

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

D Appendix: Robustness of demand estimates

a Marginal effects for alternative household profiles

DESCRIBE PROFILES AND COMPARE RESULTS

Table D6: Household Profile for Marginal Effects

Profile	Rooms	Pukka	Land	Roof	Literacy	Adults	Income (INR)
Poor	1	0	0	0	1	2	3750
Median	2	0	1	1	1	3	6000
Rich	3	1	1	1	5	5	9500

Table D7: Impact of Household Characteristics on Choice Probabilities (Median Household)

	Grid	Diesel	Own Solar	Microgrid	None
Number of adults	0.047	-0.001	0.001	0.003	-0.049
	(0.010)	(0.003)	(0.002)	(0.004)	(0.008)
Household income	0.019	0.000	0.001	0.014	-0.034
	(0.010)	(0.003)	(0.002)	(0.005)	(0.008)
Household owns land	-	-	-	-	-
Household head literacy	0.036	0.004	-0.002	0.001	-0.038
	(0.010)	(0.003)	(0.002)	(0.004)	(0.008)
Pukka (solid) house	0.098	-0.006	-0.006	-0.011	-0.075
	(0.025)	(0.008)	(0.005)	(0.009)	(0.020)
Solid roof	-	-	-	-	-
Number of rooms	0.035	0.005	0.004	0.001	-0.046
	(0.010)	(0.004)	(0.002)	(0.005)	(0.009)

The table shows the discrete effects of changes in household observable characteristics (in rows) on the probability the household will purchase different electricity sources (in columns). The household characteristics are from our survey. The changes in choice probabilities are calculated with the demand model, for which the estimated coefficients are presented in Appendix Table D11. Each cell entry is the change in choice probability for a poor household from increasing the row characteristics. For discrete household characteristics, the increase is from zero to one. For continuous household characteristics, the increase is of one standard deviation. Appendix Table D6 describes the statistical profile of a poor household and Appendix Table C3 shows the magnitude of changes in household characteristics for each variable. Standard errors are constructed using the delta method.

Table D8: Impact of Household Characteristics on Choice Probabilities (Rich Household)

	Grid	Diesel	Own Solar	Microgrid	None
Number of adults	0.036	-0.003	-0.000	0.000	-0.033
	(0.007)	(0.003)	(0.001)	(0.004)	(0.005)
Household income	0.011	-0.001	0.000	0.011	-0.022
	(0.008)	(0.003)	(0.001)	(0.005)	(0.006)
Household owns land	-	-	-	-	-
Household head literacy	0.028	0.002	-0.002	-0.001	-0.026
	(0.008)	(0.003)	(0.001)	(0.003)	(0.004)
Pukka (solid) house	-	-	-	-	-
Solid roof	-	-	-	-	-
Number of rooms	0.026	0.003	0.002	-0.001	-0.030
	(0.009)	(0.004)	(0.002)	(0.004)	(0.006)

The table shows the discrete effects of changes in household observable characteristics (in rows) on the probability the household will purchase different electricity sources (in columns). The household characteristics are from our survey. The changes in choice probabilities are calculated with the demand model, for which the estimated coefficients are presented in Appendix Table D11. Each cell entry is the change in choice probability for a poor household from increasing the row characteristics. For discrete household characteristics, the increase is from zero to one. For continuous household characteristics, the increase is of one standard deviation. Appendix Table D6 describes the statistical profile of a poor household and Appendix Table C3 shows the magnitude of changes in household characteristics for each variable. Standard errors are constructed using the delta method.

b Alternative nesting structures

Table D9: First stage results choice-specific household characteristics and nest-similarity parameter

β_{rj}	Multinomial Logit	(Grid, diesel, own solar) & (HPS)	(Grid, diesel, HPS) & (Own solar)	(Grid, Own solar, HPS) & (Diesel)	(Grid) & (off-Grid)	(Grid, Own solar) & (diesel, HPS)	(Grid/Diesel) & (Solar)
Grid × Income	0.21	0.19	0.21	0.21	0.19	0.21	0.20
	(0.06)	(0.05)	(0.06)	(0.06)		(0.07)	(0.06)
Diesel × Income	0.14	0.16	0.14	0.14	0.21	0.14	0.14
	(0.08)	(0.06)	(0.09)	(0.08)		(0.14)	(0.08)
Own solar × Income	0.17	0.18	0.17	0.17	0.21	0.17	0.19
	(0.07)	(0.06)	(0.07)	(0.07)		(0.14)	(0.08)
HPS × Income	0.49	0.48	0.49	0.48	0.22	0.49	0.43
	(0.12)	(0.11)	(0.14)	(0.13)		(0.13)	(0.14)
Grid × Land	0.24	0.20	0.24	0.24	0.24	0.24	0.24
	(0.09)	(0.08)	(0.09)	(0.09)		(0.09)	(0.09)
Diesel × Land	-0.15	-0.09	-0.15	-0.15	0.04	-0.15	-0.15
	(0.12)	(0.11)	(0.12)	(0.12)		(0.15)	(0.12)
Own solar × Land	0.15	0.18	0.15	0.15	0.07	0.15	0.15
	(0.11)	(0.09)	(0.11)	(0.12)		(0.17)	(0.11)
HPS × Land	0.22	0.22	0.22	0.22	0.06	0.22	0.16
	(0.17)	(0.17)	(0.17)	(0.17)		(0.17)	(0.14)
Grid × Adults	0.12	0.12	0.12	0.12	0.12	0.12	0.12
	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)	(0.02)
Diesel × Adults	0.09	0.09	0.09	0.09	0.09	0.09	0.09
	(0.04)	(0.03)	(0.04)	(0.04)		(0.06)	(0.03)
Own solar × Adults	0.09	0.10	0.09	0.09	0.09	0.09	0.09
	(0.03)	(0.02)	(0.03)	(0.03)		(0.06)	(0.03)
HPS × Adults	0.09	0.09	0.09	0.09	0.10	0.09	0.09
	(0.04)	(0.04)	(0.04)	(0.04)		(0.04)	(0.03)
Grid × Pukka	0.42	0.36	0.42	0.42	0.42	0.42	0.43
	(0.10)	(0.09)	(0.10)	(0.10)		(0.10)	(0.10)
Diesel × Pukka	0.13	0.20	0.13	0.13	0.10	0.13	0.17
	(0.14)	(0.11)	(0.14)	(0.14)		(0.16)	(0.15)
Own solar × Pukka	0.12	0.16	0.12	0.12	0.10	0.12	0.11
	(0.12)	(0.10)	(0.12)	(0.12)		(0.15)	(0.12)
HPS × Pukka	-0.03	-0.03	-0.03	-0.01	0.11	-0.03	0.07
	(0.19)	(0.19)	(0.21)	(0.21)		(0.20)	(0.18)
Grid × Lit	0.10	0.08	0.10	0.09	0.10	0.10	0.10
	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)	(0.02)
Diesel × Lit	0.09	0.08	0.09	0.09	0.05	0.09	0.09
	(0.03)	(0.02)	(0.03)	(0.03)		(0.06)	(0.03)
Own solar × Lit	0.02	0.05	0.02	0.02	0.05	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.03)		(0.03)	(0.02)
HPS × Lit	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	(0.04)	(0.04)	(0.04)	(0.04)		(0.04)	(0.03)
Grid × Roof	0.58	0.52	0.58	0.57	0.58	0.58	0.57
	(0.10)	(0.09)	(0.10)	(0.10)		(0.10)	(0.10)
Diesel × Roof	0.20	0.28	0.20	0.20	0.26	0.20	0.20
	(0.13)	(0.11)	(0.13)	(0.13)		(0.17)	(0.13)
Own solar × Roof	0.41	0.44	0.42	0.41	0.28	0.42	0.36
	(0.12)	(0.09)	(0.12)	(0.12)		(0.29)	(0.13)
HPS × Roof	-0.00	0.00	0.00	0.02	0.26	0.00	0.06
	(0.18)	(0.18)	(0.19)	(0.20)		(0.18)	(0.22)
Grid × Rooms	0.13	0.14	0.13	0.13	0.13	0.13	0.13
	(0.03)	(0.03)	(0.03)	(0.03)		(0.03)	(0.03)
Diesel × Rooms	0.15	0.15	0.15	0.15	0.16	0.15	0.15
	(0.05)	(0.03)	(0.05)	(0.05)		(0.10)	(0.04)
Own solar × Rooms	0.18	0.17	0.18	0.18	0.16	0.18	0.18
	(0.04)	(0.03)	(0.04)	(0.04)		(0.11)	(0.04)
HPS × Rooms	0.10	0.10	0.10	0.10	0.16	0.10	0.12
	(0.07)	(0.07)	(0.07)	(0.06)		(0.07)	(0.06)
σ_1	-	0.55	0.01	0.06	0.95	0.01	0.17
		(0.20)	(0.28)	(0.33)		(0.50)	(0.34)
σ_2	-	-	-	-	-	0.01	0.42
						(0.39)	(0.54)
σ_2	-	-	-	-	-	0.39	0.54
Number of Observations	8822.00	8822.00	8822.00	8822.00	8822.00	8822.00	8822.00
Log likelihood	-5791.35	-5789.35	-5791.39	-5791.34	-5789.26	-5791.41	-5791.32
LR test statistic	-	4.01	-0.07	0.03	4.20	-0.10	0.08
LR test p value	-	0.05	1.00	0.85	0.04	1.00	0.78

The likelihood Ratio test statistic: $LR = -2\{LL(\theta_{constrained}) - LL(\theta_{unconstrained})\}$ Each of the nested-logit specifications (columns 2 through 7) are tested against the constrained multinomial logit specification in column 1. LR is distributed $\chi 2$ with degrees of freedom equal to the number of constraints on θ. LL is the negative of the optimized objective function in MATLAB (which is defined as the negative of the sum of the individual household contributions to log of the likelihood function).

Table D10: Two-Stage Least Squares Estimates for Demand for Electricity [WILL BE UPDATED]

	(1) (Grid, Diesel, Microgrid) (Own Solar)	(2) (Grid, Diesel) (Solar)	(3) (Grid) (Off-Grid)	(4) Multinomial Logit
Price (Rs. 100)	-2.051***	-2.082***	-2.116**	-1.918**
	(0.769)	(0.775)	(0.876)	(0.746)
Hours of supply on peak	0.263	0.401	0.439*	0.437*
	(0.243)	(0.259)	(0.261)	(0.255)
Hours of supply off peak	-0.110**	-0.139**	-0.145**	-0.144***
	(0.0534)	(0.0567)	(0.0571)	(0.0555)
ξ_{tj} mean effects	Yes	Yes	Yes	Yes
Observations	1000	1000	1000	1000

The table presents 2SLS estimates of our demand system for different first-stge nest specifications. The dependent variable is mean indirect utility at the market × survey wave level retrived from the non-linear first stage. The first column, uses our preferred first stage nest-specification of grouping grid, diesel, and HPS in one nest and own-solar in its own nest. The estimates in the first column are the same as column 2 of Table 4. The second column uses a first-stage model with grid and diesel in one nest and both solar technologies in another. In the third column, we group grid in its own nest and all off-grid technologies in a second nest. In the last column, we use the mean indirect utilities derived from a multinomial logit first stage. We instrument price with our experimentally varied HPS treatment assignment. Peak hours refers to supply of electrricity during the evening (5pm-10pm). All regressions control for wave × source mean effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors cluster at the village level in parentheses.

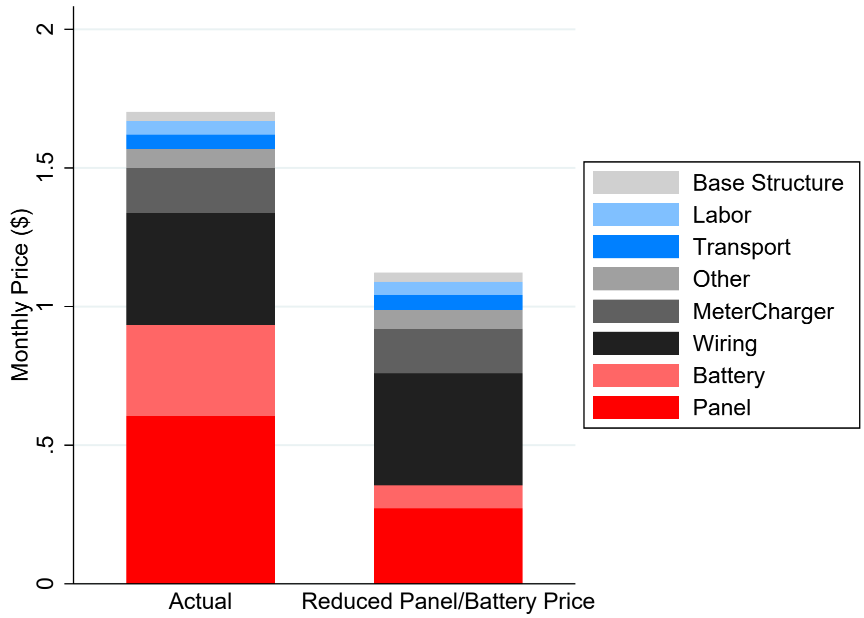
Table D11: First-Stage of 2SLS Estimates for Demand for Electricity

	Price First Stage (only price IV) (1)	Price First Stage (price and hours IV) (2)	Peak hours First Stage (3)	Off-peak hours First Stage (4)
Normal Price	0.045	0.045	0.0050	-0.0046
	(0.035)	(0.035)	(0.0050)	(0.030)
Subsidy Price	-0.14***	-0.14***	0.0075	0.014
	(0.031)	(0.031)	(0.0063)	(0.031)
Hours of supply on peak	-0.045			
	(0.045)			
Hours of supply off peak	0.0067			
	(0.012)			
Peak Hours Instrument		-0.032	0.94***	0.19
		(0.044)	(0.063)	(0.15)
Peak Hours Instrument		0.0037	0.032**	0.88***
		(0.0091)	(0.013)	(0.030)
ξ_{tj} mean effects	Yes	Yes	Yes	Yes
Observations	1000	1000	1000	1000
fstat				

The table presents the first stage estimates of the 2SLS estimates provided in column 2 and 3 of Table 4. The construction of the instrument for hours of supply is outlined in Section b. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors cluster at the village level in parentheses.

E Appendix: Counterfactual scenarios

Figure E2: Microgrid Solar Price under Current and Counterfactual Capital Costs



In our counterfactuals, we consider reductions in cost for solar photovoltaics and for batteries. We assume a 55% reduction in cost of solar PV in line with the National Renewable Energy Laboratory's for 2022. For batteries, we assume a cost reduction of 75% in accordance with the US Department of Energy's 2022 goal.

Table E12: Counterfactual Analysis: Assumptions

Scenario	Source availability	Source hours (peak)	Source price
		Panel A: Theft Reductions	
Data			
Model	Endline 1	Endline 1	Endline 1
		Panel B: Value of solar innovation	
Solar nowhere	Endline 1 for grid and diesel, solar nowhere	Endline 1	Endline 1
Solar everywhere	Endline 1 for grid and diesel, solar everywhere	Endline 1	Endline 1
Solar cost falls	Endline 1 for grid and diesel, solar everywhere	Endline 1	Reduction in HPS price from INR 170 to INR 120, according to the "solar cost falls" scenario in Figure 7. Own solar price is proportionally decreased.
Further solar innovation	Endline 1 for grid and diesel, solar everywhere	Endline 1	Own solar: 55% reduction in solar panel cost (NREL Fig 8, low estimates, pp. 17) and a 75% reduction in batteries (DOE, pp. 2). Panel is 36% of total cost and batteries is 19% of total cost. These numbers imply a reduction in total own solar price by 34%. Mean own solar price is reduced by 34%. All other solar costs (meter charger, wiring, labour, transport, other are assumed constant). Mean HPS price is similarly reduced by 34%. Prices of all other sources are according to endline 1.
		Panel C: Grid Extension	
Grid nowhere	Endline 1 for solar and diesel, grid nowhere	Endline 1	Endline 1
Grid Everywhere	Grid everywhere, endline 1 for diesel, solar everywhere	Endline 1	Endline 1
Grid 2 extra peak hours	Endline 1 for grid and diesel, solar everywhere	Two additional peak hours for grid, endline 1 peak hours for all other sources.	Endline 1
		Panel D: Theft Reductions	
Remove theft by raising grid price	Endline 1 for grid and diesel, solar everywhere	Endline 1	Grid at INR 140, all else at endline 1. The grid price was derived as follows: grid price in the model estimation is presently defined as the reported bill value in the surveys multiplied by payment rate, where payment rate is the mean of the responses to “Do you pay your bill?" in the endline 2 survey. We therefore define the “remove theft" counterfactual by using the reported bill value as full price un-scaled by payment rate. This yields INR 140."
Increase peak supply and raise prices	Endline 1 for grid and diesel, solar everywhere	Grid peak hour = 5 hours everywhere, all else at endline 1	Grid at INR 95 everywhere, all else at endline 1. INR 95 is derived as follows: grid peak supply is set to 5 hours everywhere. Price is set so that total loss per HH in the endline sample is equal to that obtained in row 3 (model with solar everywhere).

Note: Household characteristics and source off-peak hours are unchanged (at their endline 1 levels) across all counterfactual cases and hence omitted from the table.