Demand for Electricity on the Global Electrification Frontier*

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Abstract

Falling off-grid solar prices and subsidized grid extension are revolutionizing choice for the billion people without electricity. We use experimental price variation to estimate demand over *all electricity sources* in Bihar, India, during a four-year period when electrification rates leapt from 27% to 64%. We find that household surplus from electrification tripled, with gains due nearly as much to off-grid solar as to the subsidized grid. Choice matters—the surplus from electrification is 3-5× greater than from any one source. Nonetheless, we project future electrification will come mainly from the grid, since households prefer the grid as they grow wealthier.

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The global electrification frontier is the collection of places in the world where, at a given time, households are getting electricity for the first time. The steady movement of this frontier, in the United States from 1935 onwards, Brazil from the 1960s, China in the 1980s, and much of South Asia and sub-Saharan Africa in the 2000s up through today, has been inseparable from structural change and economic growth. In pursuit of growth, many developing countries are investing large sums to build out their distribution infrastructure and subsidize connections, to reach the roughly one billion people who are still not on the electricity grid (International Energy Agency, 2017).

The rapid decline in the cost of solar panels, however, has changed the shape of the global electrification frontier. In the traditional mode of electrification, the frontier was a literal boundary, defined by the extent of the grid, with households filling in behind it (Lee et al., 2014). Solar panels can supply the grid, but, unlike other sources of power, they can also generate relatively efficiently at a small scale, on the roof of a single household. The frontier today has therefore dissolved and permeated rural areas. A rapid decline in solar costs has opened up a new mode of electrification, whereby every household can choose whether to get solar power, regardless of whether the grid has reached them. The advent of off-grid solar has thus spurred hope of a faster, greener path to universal electrification.[1] This optimism has a real justification: over the last decade, off-grid solar's market share on the global electrification frontier has skyrocketed (Figure 1).

The convergence of "big push" grid expansions and off-grid solar means that many households in developing countries now have a choice between competing electricity sources. This paper estimates the demand for electricity, over *all available sources* of electricity, in order to understand how poor households are making this choice. We seek to measure the value of electrification and to attribute this value to the changes in technology and policy that are taking place on the frontier.

Our setting is Bihar, India, a typical outpost on the global electrification frontier. Between 2000 and 2016, India contributed over 80% of the total gain in the number of households in the world connected to the grid (International Energy Agency, 2017). While the grid has expanded rapidly,

[1] 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." ("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.) UN Sustainable Development Goal #7 is to "ensure access to affordable, reliable, sustainable, and modern energy" and targets increasing the share of renewable energy in the global energy mix in particular. 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.

electricity in the state of Bihar, as in many developing countries, remains a differentiated product: there are several sources of electricity, including both the public grid and private off-grid sources, which differ in price, load, hours of supply and other features.

We model the demand for electricity with a discrete choice demand model (McFadden, 1974; Lancaster, 1971), to capture the choice between technologies that is the defining feature of household electrification in many developing countries today. Households choose between four electricity sources—the grid, diesel generators, solar microgrids, and their own off-grid solar systems—and an outside option of no electricity. We allow for substantial observed heterogeneity in household demand and source characteristics. We also allow the unobserved quality of different electricity sources to vary without restriction across villages and time (Berry, 1994). This feature is critical for us to capture rapid changes in the quality of goods like off-grid solar power.

We estimate the demand model using an experiment that introduced a new product, solar microgrids, and varied its price across 100 village-level markets for two and a half years. The availability of experimental variation in price to estimate a discrete choice demand model is extraordinarily rare and removes the need to rely on traditional assumptions, about market conduct or the structure of demand shocks, to generate instrumental variables (Berry, Levinsohn and Pakes, 1995; Hausman, 1996; Nevo, 2001). Our experiment varies price over the medium-run, which removes external validity concerns that arise with short-run discounts. In our setting, we find that the experimental variation is necessary to recover unbiased and precise estimates of the price elasticity of demand.[2]

To place the experiment within a broader context, we collect comprehensive data on the demand and supply sides of the village electricity markets in our sample over the four years from 2013 to 2017. During this period electrification increased by almost *40 percentage points*. As a basis of comparison, this surge in electrification occurred in half the time it took to increase electrification rates by the same amount in the rural United States, after the passage of the landmark Rural Electrification Act in 1936.[3] The gains in electrification in Bihar were due to the same two factors, the advent of off-grid solar and a "big push" on the grid, that are reshaping electrification around

[2]The experimental estimates of the price coefficient are negative, large and stable across specifications. If we instead estimate the price coefficient using ordinary least squares, it is negative and precisely estimated, but smaller than the experimental estimate by a factor of seven. Traditional instruments from the industrial organization literature are found to have no power in our setting (Berry, Levinsohn and Pakes, 1995; Hausman, 1996; Nevo, 2001).

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

the world. Our setting therefore allows us to use experimental estimates of demand to value historic changes in energy access that are externally relevant for the experience all along the global frontier.

We have three main findings. First, the increases in energy access observed during our sample period tripled the household surplus from electrification. With the demand model, we can isolate the reasons for this gain, and find that the advent of off-grid solar alone would have increased surplus by $2.2\times$ and the "big push" of the electricity grid alone by $2.6\times$. In our study period, the grid extended from 29% to 72% of villages and connection costs for households below the poverty line were subsidized to zero. It is a testament to the advances in solar technology that private, off-grid solar, on its own, would have created three-quarters as much surplus ($= (2.2-1)/(2.6-1)$) as this enormous and highly subsidized expansion of the traditional grid.

Second, choice matters: the household surplus from electrification, from all sources of electricity, is three to five times greater than the surplus due to any single electricity source. The reason is that households readily substitute between several sources that offer similar energy services at similar prices, although they are differentiated on dimensions like the load they support and hours of supply. In our full demand model, the elasticity of demand with respect to price for off-grid sources of electricity ranges from -1.5 to -1.8. Put plainly, households' choices show that they find available sources similar and will take up any source that meets certain basic needs at the right price.

Third, future growth in electrification will come mainly from the grid, since households prefer grid electricity as they become wealthier. This finding is a direct implication of our demand estimates, in which households with a solid roof, a common indicator for wealth, have roughly *double* the probability of choosing grid electricity as households without. Wealthier households' preference for the grid likely stems from their wish to run higher load appliances, like fans and televisions, which off-grid sources usually do not support. To forecast the future path of electrification in Bihar, we run a counterfactual where solar costs continue their decline, the grid reaches all villages, the number of hours electricity is available on the grid increases and all households achieve at least the 80th percentile of sample income and assets.[4] In this scenario, *all* new electricity connections, on net, are grid connections, despite the continued fall in the price of solar.

While growth in incomes will tilt demand towards the grid, whether the grid will dominate

[4]These changes are large, but plausible in our dynamic context, and still raise household income in our sample only to parity with the per capita GDP of Malawi, one of the world's poorest countries.

future electrification to the degree we forecast depends on policy towards subsidies. Bihar, like many countries on the global frontier, subsidizes household electricity use. Such subsidies are a durable aspect of policy, sustained by several strong forces, including the political economy of redistribution through energy (Burgess et al., 2020). Nevertheless, they place fiscal stress on governments, and so we consider a counterfactual where the state scales back subsidies as demand for electricity grows. In this scenario, households' price sensitivity and the fluid substitution between sources lead to marked switching from the grid to solar and modest reductions in overall electrification rates and surplus. The path of electrification running mainly on the grid therefore depends on the state's continued willingness to bear energy subsidies as it approaches universal electrification.

Our paper makes two contributions to the literature on electricity access in developing countries. First, we study household demand for electrification, a revealed-preference measure of the value of electricity, whereas most of the literature has measured the impact of access to electricity on a range of economic and welfare outcomes.[5] Second, we estimate how households value both grid and off-grid electricity together, in a single demand system, which allows us to study substitution between sources. Other papers have estimated the demand for individual sources of electricity, rather than electricity generally, leaving the choice set and the pattern of substitution unspecified.[6,7]

More broadly, this study joins a methodological movement in the development literature that combines structural models with experimental variation to aid in the interpretation and increase the external validity of experimental results.[8] Our study combines experimental price variation with a structural demand model allowing rich observed and unobserved heterogeneity. Our finding on the large gap between the value of electrification and the value of any one electricity source shows the

[5]Prior work has found that electricity access causes large increases in labor supply (Dinkelman, 2011), industrial output (Rud, 2012; Allcott, Collard-Wexler and O'Connell, 2016), manufacturing productivity (Kline and Moretti, 2014), agricultural productivity (Kitchens and Fishback, 2015), land values (Lewis and Severnini, 2019), and proxies for household welfare, such as the human development index and indoor air quality (Lipscomb, Mobarak and Barham, 2013; Barron and Torero, 2017). See Lee, Miguel and Wolfram (2020*a*) for a review of the impacts of electrification.

[6]In contemporaneous experiments, Lee, Miguel and Wolfram (2020*b*) estimate demand for grid connections in Kenya and Grimm et al. (2020) estimate demand for off-grid solar technologies in Rwanda. Aklin et al. (2018) study how household characteristics predict solar take-up in India.

[7]A couple papers have hypothesized that solar and grid electricity are imperfect substitutes for the rural poor. Fowlie et al. (2019) suggest that a promise of future grid connections, in Rajasthan, India, may have reduced the take-up of off-grid sources like microgrids. Lee, Miguel and Wolfram (2016) report the results from a household survey in Kenya showing that grid users own more high-load appliances than solar users.

[8]Examples include studies that use experiments to help estimate structural models of fertility, education, labor supply, migration and human capital, and enforcement of plant emission standards, though not demand for electricity (Todd and Wolpin, 2006; Attanasio, Meghir and Santiago, 2012; Duflo, Hanna and Ryan, 2012; Bryan, Chowdhury and Mobarak, 2014; Galiani, Murphy and Pantano, 2015; Duflo et al., 2018; Attanasio et al., 2020).

value of a structural model for placing experimental estimates of demand, for any given product, in the context of the broader product market. Our paper is therefore related to the literature in industrial organization on estimating the value of new products (Hausman, 1996; Petrin, 2002; Goolsbee and Petrin, 2004). Experimental work in development economics tends to estimate the demand for one product at a time, which may, as in our case for electricity, greatly understate the demand for the categories to which products belong.[9]

1 Background and Data: The Electricity Landscape in Bihar

This section introduces our data and describes the electricity market in Bihar, India, a state of 104 million people (Census of India, 2011).

Bihar is one of India's poorest states and, at the start of our study period, had very low access to electricity. Table 1 juxtaposes the United States, India, sub-Saharan Africa and Bihar on the dimensions of income and access to electricity circa 2012 (our baseline survey was conducted at the end of 2013). The electrification rate in Bihar at this time was only 25%, below the rate of 37% in sub-Saharan Africa and about one-third of the all-India rate of 79%. The average Bihari used just 122 kWh of electricity per year, less than one percent of the level in the United States (column 4, last row). At this level of consumption, which is an average, including many households with no electricity at all, a person can power two light bulbs totaling 60 watts for six hours per day. The low level of 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.

Our study, luckily, was well-timed to capture two big changes in the electricity market. First, beginning before and carrying on through our study period, the continued decline in the price of solar panels made off-grid solar a feasible alternative to grid power. Second, in response to low rates of electrification in states like Bihar, the Government of India funded large campaigns for grid

[9]Experimental estimates of demand have been an enormous area of growth in development economics and are used both to test theories of behavior and to consider optimal policy. Preventive health products (Berry, Fischer and Guiteras, 2020; Peletz et al., 2017; Dupas, 2014) and financial services (Bertrand et al., 2010; Karlan and Zinman, 2018, 2019) are two prominent markets in which experiments have been used to estimate demand. Though many products in these markets arguably have close substitutes, few studies that experimentally estimate demand explicitly model substitution. Kremer et al. (2011) is a close precedent that experimentally varies the quality of a good, a local water source, and estimates a demand model using observable variation in walking distance to water sources as a proxy for price.

extension and household connections.

a Data

We collect data from both the demand and supply sides of the market over a nearly four-year period. Our sample consists of 100 villages in two districts in Bihar (Figure 2). The study villages were sampled from a set chosen to have low rates of electricity access at baseline.[10]

We collect data from four sources. First, on the demand side, a household-level panel survey on the sources and uses of electricity. Second, on the supply side, household-level administrative data on customer enrollment and payments from HPS. Third, on the supply side, village-level survey data from the operators of common diesel generators, an off-grid source of electricity. Fourth, on the supply side, household-level administrative data from the state utility on customer billing and payments, as well as village-level electricity supply. We describe the household panel survey here and the rest of the data sources in Appendix A.

Our household panel survey sampled 30 households per village to cover about 3,000 households, containing about 18,000 people, 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.[11]

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 (Appendix Figure A1 shows the timing of survey rounds). 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

[10] Low access was defined as on three criteria. First, they were not listed as electrified villages by the government, meaning that household grid electrification was below ten percent and at least one neighborhood of the village was not on the grid at all. 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 facilitate a possible expansion of microgrids, villages were chosen to be reasonably close to existing HPS sites. We selected 100 villages that met these criteria, which have a total of 48,979 households. A number of the study villages, in West Champaran district, are clustered near the border between Bihar and Uttar Pradesh, with one village being part of Uttar Pradesh.

[11] 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 were 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.

electricity use. The follow-up round took place one year after the endline for the experiment and was not part of our original plan. The purpose of this round was to update household electricity sources and choices, in light of the massive changes we observed on the supply side. The baseline and follow-up rounds are separated by three and a half years.

b Characteristics of electricity sources

In developed countries, electricity is the archetype of a homogeneous good: power is available from the grid 24/7/365 and can run all kinds of appliances. In Bihar, as in many developing countries, electricity connections are differentiated products. This part describes the characteristics of different electricity sources in our sample.

Table 2 describes each electricity source qualitatively on several dimensions that matter for household choices, such as availability, energy services and reliability. There is one on-grid electricity source: grid electricity, provided by a state-run distribution company (column 1). There are three off-grid electricity sources: microgrid solar, own solar, and diesel generators, all provided in private markets (columns 2 through 4). A solar microgrid is a solar system, consisting of a solar panel and batteries, that serves a small group of six to nine households.[12] An own solar system is a panel and battery bought and operated by a single household. A diesel generator, in our context, is a generator set up by an entrepreneur and run with diesel fuel to supply electricity to a large group of households in a single village. Diesel generators serve 100 customers on average, with a range from 60 to 200 in our sample. The outside option for households is not to have electricity from any of these four sources, which means they then rely on kerosene for lighting (column 5).

Grid electricity is only available if a village is on the grid, and then only after an application process to grant a connection (column 1). Off-grid electricity sources, described in columns 2 through 4, are offered in private markets and therefore can be sold whenever demand is great enough to justify their costs. Off-grid sources are limited in the load—the power drawn by connected appliances—they can serve, and so typically provide only lighting and phone charging, the basic energy services

[12] The microgrids in our context are offered by Husk Power Systems, our partner in the experiment. The HPS microgrid consists 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. To compensate for the small load, 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.

that all households demand from an electricity source.

Though all the off-grid electricity sources provide similar energy services, there are important differences between them in availability, set-up costs, contracts, maintenance, and the risk of disconnection. For example, households purchasing an own solar system pay up-front and would usually have to travel to a market town to buy a system, made up of a panel, a battery, and sometimes a socket to plug in and switch appliances (column 3). Since the system is owned outright, households face no risk of disconnection after purchase. Households with a solar microgrid or diesel connection pay the private operators of those services on a monthly basis and may therefore be disconnected for non-payment (columns 2 and 4). An offsetting advantage of these sources, relative to own solar systems, is that the provider, rather than the household, is responsible for set-up and maintenance. These kinds of differences between sources suggest that there are a number of reasons, some of which are difficult to measure, as to why a household may prefer one source to another.

Table 3 supports this qualitative comparison with summary statistics on the characteristics of electricity sources at baseline (columns 1 through 5), endline (columns 6 through 10) and follow-up (columns 11 through 15). Panel A reports on source characteristics: monthly price, the total connected load of appliances a household using each source has plugged in, hours of supply, in total and during peak and off-peak hours, and the share of villages in which a source is present.[13] We highlight four findings that characterize the trade-offs households face in choosing a source.

First, the grid can support higher loads and therefore a wider range of energy services than other sources. Most households connected to any electricity source own mobile phones and light bulbs (Table 3, panel B). Among grid-connected households, in addition, 22 percent own a fan and 15 percent a television, whereas few households with other sources of electricity own these appliances. Households on the grid have a mean connected load of 322 watts, 30% larger than the second-highest load source (panel A, comparing columns 1 through 4).

Second, the grid is not as reliable as other sources during the evening peak, when households most want electricity. The mean grid supply in the peak hours, from 5 to 10 pm, was only 2 hours per day at baseline and endline, increasing to 3 hours at follow-up. Even this low average understates the trouble with grid supply, since on one day out of four there is no grid supply at

[13] Properly, the connected load of appliances 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 capped by the load a source can support.

all (Appendix Figures A2 and A3 show the distributions of hours of supply for the grid, in total, off-peak and on-peak). All other sources of power provide more supply during the peak hours in all survey waves.

Third, the pricing in the market is fairly tightly clustered. At baseline, three sources have average monthly prices from INR 72 to INR 99 per month (Table 3, panel A, columns 1 to 3).[14] The highest-priced product, above this tight cluster, is microgrids, with a price of INR 200 per month. Our experiment later subsidized the price of this product (see Section 2 a). The tight clustering of both energy services and pricing across disparate sources in the baseline data gives a sense that the retail electricity market in Bihar is quite competitive.

Fourth, the availability of different sources changed dramatically over the nearly four years of our data collection. The grid was present in 29% of all villages at baseline (Table 3, panel A, column 1), 53% at endline (column 6) and 72% at endline. The availability of diesel *fell* from 57% (column 2) to 13% of villages (column 12) in the same span, predominantly because it was losing to the grid in the marketplace. We assume that own solar systems are available in all villages, since households can travel to buy these systems.

c The two disruptions in Bihar's electricity market

The electricity landscape in Bihar, as these statistics on availability suggest, was transformed during our study. The two changes underlying this transformation, on the supply side, are a fall in the cost of solar power and a surge in grid extension and connections.

The first force changing the electricity landscape is a fall in the price of solar power. The price of solar power has been declining rapidly for several decades, but only in the last decade has it reached a level low enough to make off-grid solar a viable choice for poor people (Figure 1). Our data reflects these trends. The price of own solar systems fell 10% during our data collection from INR 80 at

[14] Households pay up front for home solar systems, so we have amortized the cost of these systems into a monthly price equivalent. For own solar, household systems, once purchased, 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 lifespan of seven years and a 20% interest rate. For the grid, we take the monthly price to be the self-reported monthly payment for grid electricity, averaged across formal and informal households on the grid. Grid electricity is in principle charged on a volumetric tariff; however, a minimum monthly payment and infrequent meter reading imply that many poor consumers are *de facto* billed at a flat monthly rate. The *de facto* grid price is INR 72 per month at baseline and INR 60 at endline. Informality acts as a large price cut for the grid. Of the 158 households using the grid at baseline, only 47% answered yes to the question "Do you pay electricity bills?" The full grid price of INR 153 per month at baseline, if everyone paid their bills, would place it amongst the most costly sources, while at INR 72 per month, it is one of the cheapest.

baseline to INR 72 at follow-up. This lower price is likely not for the same energy service, but a better one. Solar vendors entered smaller towns closer to villages, effectively lowering connection costs. Quality may also have improved as solar panels got more efficient and batteries more reliable.

The second force was a "big push" policy on grid electrification at both the national and state levels. In his 2015 independence day address, Indian Prime Minister Narendra Modi launched a rural electrification program with a thousand-day deadline to electrify the remaining 18,452 census villages still without access, at an estimated cost of USD 11 billion.[15] When the grid reaches a village, poor households may not connect, or may take a long time to do so (Lee et al., 2014). The Government of India therefore started a complementary USD 2.5 billion program to subsidize states in providing infill household connections in electrified villages.[16]

In Bihar, the state government made electricity access a priority (Kumar, 2019). Nitish Kumar, Bihar's six-time Chief Minister, invested heavily in grid electrification, using both central and state funds, and promised universal household electrification as part of his reelection campaign (Business Today, 2017). During our four-year study period, the state's own data report giving out over 7 million electricity connections, representing a staggering 51 pp increase in the statewide household grid electrification rate. The government not only invested in infrastructure, to extend the grid, but also held camps to sign-up households and heavily subsidized connections, including by offering connections for free to all households designated as Below the Poverty Line (BPL). The heavy state investment in this period allowed the grid to reach progressively poorer households.[17]

[15] The village-level goal was declared achieved ahead of schedule on April 28, 2018. A village is defined as electrified once public spaces, such as schools and health centers, have access to electricity, along with a minimum of 10% of its households. 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 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).

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

[17] Appendix Table A1 shows comparisons of household characteristics by the timing of grid arrival in a given village, within our survey sample. Villages that got the grid earlier are significantly richer than villages that got it later. In villages that got the grid earlier, households are twice as likely to have a solid house, more likely to have a solid roof and have more educated household heads. Households in villages that got the grid earlier also have higher access to electricity, from any source, at baseline. This finding is not purely a mechanical effect, due to grid presence, but may reflect underlying differences in household demand. For example, "grid late" villages, which did *not* have the grid at the time of our baseline survey, but got it before our follow-up survey, nonetheless have greater electricity access *at baseline* than "no grid" villages; this higher initial access is provided by diesel generators, and not the grid itself.

d Market shares of electricity sources in Bihar

The two disruptions of solar and grid expansion transformed electricity access during our study. Figure 3 shows the market shares of all electricity sources over time. Each stacked bar gives the share of households, from bottom to top, that use grid electricity, diesel generators, solar microgrids, own solar systems or no electricity. Market shares are calculated with respect to the total sample, regardless of whether a source is available in a village or not; in a village where the grid is not present, for example, the grid necessarily has a zero share. There are three clusters of bars, for shares in the baseline, endline and follow-up survey waves. Within each cluster of bars, the three bars from left to right give the market shares amongst all households, households that do not have a solid roof, and households that do have a solid roof, respectively. Whether a household has a solid roof is commonly used to measure wealth (Alatas et al., 2012; Haushofer and Shapiro, 2016)

Household electrification surged during our study period. Consider the left bar in each group, for all households. The electrification rate from any source, the sum of the colored bar stacks, increased 37 pp, from 27% to 64%, in somewhat less than four years.

The net gain in electrification conceals the churning of market shares across sources. Diesel generators, the black bar segment (second from bottom), were the most popular source of electricity at baseline, with 17% market share (despite being available in only 57% of villages). By endline, diesel had all but disappeared. Grid electricity (the bottom bar segment, in brown), by contrast, surged, with market share rising from 5% to 25% and then 43%, in successive surveys. No village in our sample had a grid take-up of over 50% at baseline, but 44% did by the follow-up survey. Solar microgrids (third from the bottom, in yellow) also increased their share, from nothing to 9% at endline, when subsidies were still offered as part of our experiment, but fell back down a year later. Own solar systems (top colored bar, in orange) picked up the slack, rising from a 5% share at baseline to a 15% share at follow-up, with all of their growth coming between the endline and follow-up rounds.

Figure 3 also shows significant heterogeneity in household electricity sources within a given survey wave (cluster of bars). At baseline, the electrification rate among households without a solid roof is little more than half that for households with a solid roof. The two disruptions increased electrification rates for both groups and narrowed this divide, though a gap in electrification rates of 15 pp remained at follow-up. The heterogeneity across households also extends to technology choice; households with a solid roof are much more likely to have grid electricity, whereas they are somewhat less likely, compared to households without a solid roof, to have off-grid solar.

The transformation of Bihar's electricity sector thus has three aspects. First, a surge in the overall electrification rate. Second, a compositional shift, away from diesel and towards solar power and especially grid electricity. Third, heterogeneity in household demand, with richer households more likely to have electricity from the grid at any given time.

2 Demand for Solar Microgrids

This section describes our experiment and uses the experimental variation to estimate demand for solar microgrids. The demand for microgrids is important, in its own right, because off-grid solar has emerged as a widespread substitute for grid electricity on the global electrification frontier. We use the demand estimates to calculate the contribution of microgrids to household surplus.

While we start by estimating demand for this new good, microgrids are only one of several competing electricity sources in Bihar (Section 1). Therefore, Section 3 will use the same experimental variation that we introduce here to estimate a richer model of demand over all electricity sources.

a Experimental design

The falling price of solar has made solar-as-a-service a newly viable business. Husk Power Systems (HPS), a social venture company that supplies off-grid power to villages in Bihar, decided to add the solar microgrid product to its portfolio as a means of reaching a wider set of customers.[18] HPS was the only microgrid provider, to our knowledge, in our sample, and so we treat HPS and microgrids as synonymous hereafter.

We partnered with HPS to vary the availability and price of solar microgrids in a cluster-randomized control trial at the village level. We randomly assigned sample villages into one of three arms: a control arm (34 villages) where HPS did not offer microgrids, a normal price arm (33 villages) where HPS offered microgrids at the prevailing price, initially INR 200 per month, and a

[18] HPS was founded in 2007 to provide electricity in rural areas using biomass gasifiers as generators, fueled by agricultural waste, such as rice husks (hence the name of the company). These biomass plants were subject to fuel supply disruptions and could only serve a village if demand was sufficiently broad.

subsidized price arm (33 villages) where HPS offered microgrids at a price of INR 100 per month. The normal price arm provides microgrid service at, or slightly above, cost and the subsidized arm at perhaps 40% below cost.[19] Within each treatment village, all households were offered the same HPS connection and pricing, regardless of whether they had previously expressed interest in a microgrid or participated in our baseline survey. Sales of microgrid connections began in January 2014, right after the baseline survey.

The treatment assignments set the initial prices in all villages. Prices of microgrids thereafter changed for two reasons. First, the prevailing or normal price arm was not rigid, but was meant to capture the price at which HPS would offer microgrids, if there had not been an experiment. Husk Power, due to low demand at the initial price of INR 200, endogenously chose to cut prices to INR 160 in 11 villages in the normal price arm. Second, the experiment ended with our endline survey, in May 2016, but our data collection runs beyond this survey. After the completion of the experiment and our endline, but before the follow-up survey, Husk Power set the price in all 66 treatment villages to INR 170 per month.[20] HPS did not enter the control villages at any point during our study period. In the demand analysis, we use treatment assignments, and their interactions with survey wave indicators, as exogenous instruments for price.

Table 4 shows the balance of household covariates in our sample including 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. Table 4, column 1 gives household characteristics in the control group. Our rural sample is poorer than the population of Bihar as a whole. Self-reported household incomes imply mean per capita daily income of INR 43 (USD PPP 2.5) at baseline, compared to mean per capita daily income of INR 99 (USD PPP 5.8) across the state.[21] Two-thirds of households own agricultural land and less than half have a solid roof.

[19]We estimate the capital and installation costs of a microgrid to be INR 105 per household per month (Appendix Figure C4). 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 costs in the range of INR 160 to INR 200 per month, the range of prices offered in our normal price arm.

[20]This price adjustment meant that 22 normal price villages experienced price declines of INR 30 (from 200 to 170); 11 normal price villages experienced a INR 10 increase; and all 33 subsidized price villages saw a substantial increase of INR 70 (from 100 to 170).

[21]Using a Gross State Domestic Product (GSDP) of Rs 36,143 for year 2014-15 (Bihar State Government, 2015), and a INR per USD PPP rate of 17, per OECD Data for India for 2014.

Table 4, columns 4 and 5 show the differences between normal price and control arms and between subsidized price and control arms, respectively, with standard errors in parentheses. 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. We address this slight imbalance by including household covariates as controls in our demand estimates.

b Demand estimates

Table 5 presents estimates of microgrid demand. In the first three columns, we give intention to treat (ITT) estimates that regress microgrid market shares in village v in period t on the experimental treatment assignments:

$$s_{Microgrids,tv} \quad = \quad \beta_0 + \beta_1 T_v^{Subsidized} + \beta_2 T_v^{Normal} + \epsilon_{tv}. \tag{1}$$

The coefficients in the first two rows report the change in market shares for solar microgrids due to the subsidized and normal price treatments, respectively, and the constant gives the market share of microgrids in the control group. Columns 1 through 3 report estimates for different periods: the baseline (November 2013), endline (May 2016) and follow-up surveys (May 2017), respectively.

The first finding in Table 5 is that the experiment increased solar microgrid penetration. We expect there should be zero take-up at the baseline, because microgrids were a new product, about to be launched. At baseline, in column 1, the estimated constant, representing take-up in the control group, and the estimated normal price and subsidized treatment coefficients are very small and statistically not different from zero. At endline, in column 2, the estimated constant was 2.3 pp (standard error 0.5 pp), and the coefficient on the subsidized price treatment shows that it increased solar microgrid take-up by 19.3 pp (standard error 4.9 pp). The coefficient on the normal price treatment is considerably smaller (6.0 pp, standard error 2.8 pp), showing the sensitivity of household take-up to microgrid prices. We find a similar gap in estimated demand when using administrative measures of household payments, rather than surveys, to measure take-up.[22]

[22] We have administrative data from Husk Power that contains the monthly payment history of all eligible households. Appendix Table B11 repeats the demand analysis from Table 5 with these administrative data at baseline and endline, as well as for a separate measure of whether a household ever paid for a Husk solar microgrid. At the endline,

The second finding in Table 5 is that solar microgrid shares fell sharply between endline and follow-up, after experimental subsidies were withdrawn. By the follow-up survey, relative to the experimental endline one year prior, the solar microgrid market share in the subsidized price villages had declined by more than 11 pp (58%), and in the normal price villages by 4 pp (67%). In the subsidized treatment arm, the increase in price after the experiment ended must have cut market share sharply. However, the decline in market shares, proportionally, was just as large in the normal price treatment arm, which did not experience a large change in price after the experiment. This similarity across the two treatment arms suggests that the expiration of subsidies does not explain the entire fall in microgrid market shares, which we investigate further in Section 3 c.

The last two columns of Table 5 give instrumental variables estimates of microgrid demand, where we instrument for the price level (or log of price) using the experimental treatment assignment. For example, the column 4 (linear) IV specification of demand consists of the two stages

$$s_{Microgrids,tv} = \beta_0 + \beta_1 Price_{tv} + \epsilon_{tv} \tag{2}$$

$$Price_{tv} = \alpha_0 + \alpha_1 T_v^{Subsidized} + \eta_{tv}. \tag{3}$$

A corresponding log-log specification is used in column 5. The sample for these columns is limited to the two-thirds of villages in which microgrids were offered. Consistent with the ITT estimates, we find large, negative and highly significant effects of price on microgrid market share in both linear and log-log specifications of demand. The linear demand estimates imply a choke price, at which demand for the product is zero, of INR 270, with demand increasing by a 0.129 share (standard error 0.052) for each INR 100 cut in price.

c Surplus from microgrids

We use these experimental demand estimates to calculate the contribution of microgrids to household surplus. The value of a new good is the consumer surplus it creates, the area under the demand curve above the price at which it is offered. Let $P(Q)$ be inverse demand, $Q^*_{tv} = P^{-1}(Price_{tv})$ be

we observe that about 18 pp (standard error 5.2 pp) of subsidized treatment households and 1.3 pp (standard error 1.0 pp) of normal treatment households are recorded as customers for solar microgrids. We believe the demand estimates from the administrative data are slightly smaller than in the survey, in the normal price treatment arm, because there was a lag between the time when households stopped paying, and hence removed from the administrative records as a customer, and when they were physically disconnected. The baseline results in the administrative data are also similar to the survey baseline results. We do not have access to the administrative data at the time of the follow-up.

the quantity purchased and $\underline{Q}$ be the small quantity that would be purchased at the choke price ($= 0$ for linear demand, and taken as P^{-1}(INR 500) for isoelastic demand). We calculate annual consumer surplus at a monthly price $Price_{tv}$ as

$$CS = 12 \int_{\underline{Q}}^{Q^*_{tv}} (P(Q) - Price_{tv}) dQ. \tag{4}$$

With Q measured in market shares, this yields surplus per household over all households, regardless of whether or not they purchased microgrid services.

Table 6 reports estimates of the value of microgrids. Columns 1 and 2 report estimates of surplus using the Table 5, column 4 (linear) and column 5 (log-log) demand specifications, respectively. In panel A, we evaluate the surplus if microgrids were offered at a uniform, subsidized price of INR 100 per month. Panel B evaluates surplus from microgrids at the actual prices at which they were offered at endline (1/3 of villages at INR 170, 1/3 at INR 100, and 1/3 not offered). We will return to discuss columns 3 and 4 in Section 3, where we compare the results from this simple demand specification with those from our full demand model.

Microgrids are a new means of electricity access, but their limited market shares and our elastic demand estimates imply that they generate only modest gains in surplus. At the subsidized price, microgrids increase surplus by INR 222 or INR 242 per household per year (panel A, columns 1 and 2), depending on the demand specification used. At the actual prices and availability (panel B), as of the endline survey, microgrids give surplus of INR 91 or INR 129 per household per year. The surplus of INR 91, calculated from the linear demand curve estimates, is 1.6% of household energy expenditure in our sample. Because roughly one in ten households purchased microgrids, surplus per microgrid user is higher by about a factor of ten.[23] The surplus estimates are fairly similar for our two different specifications of demand.

The demand for one source of electricity will be a bad proxy for the demand for electricity, on the whole, if there are close substitutes available for any given source, as we have argued is the case in Bihar's competitive electricity market (Section 1). The availability of substitutes affects both the interpretation and the external validity of our estimates. On interpretation, internally-

[23]The surplus numbers for the hypothetical removal of microgrids are also understated in the sense that they give the effect of removal relative to the status quo at the time of the endline survey. In this status quo, microgrids are not present in the control group, one-third of sample villages, to begin with. Thus the removal of microgrids, by design, has no effect on surplus in those villages.

valid estimates of microgrid demand cannot tell us household willingness to pay for the product category *electricity*, even within the context of the experiment, when close substitutes are available. Households may value electricity, but have elastic demand for microgrids, if, when microgrid prices rise, they can buy another source of electricity they prefer. On external validity, household demand for microgrids may have been drastically different in a different policy or supply environment, for example, if the government had not made a big push for the grid, or if the price of alternatives like own solar had not declined. In the following sections, therefore, we will specify and estimate a demand model that covers *all* electricity sources.

3 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 key parameters. First, our data is a household panel survey, so we specify demand to depend on a rich set of observable characteristics at the household level. Second, we allow the unobserved quality of all electricity sources to vary without restriction across villages and time (Berry, 1994). Third, we use the experimental variation in microgrid prices across markets, at the village-by-survey wave level, to estimate household sensitivity to prices.

a Specification

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

$$\begin{aligned} U_{ijtv} &= \delta_{jtv} + z_{it}'\gamma_j + \epsilon_{ijt} && (5) \\ &= V_{ijtv} + \epsilon_{ijt} && (6) \end{aligned}$$

The term V_{ijtv} is the strict utility of a choice for a household absent their idiosyncratic taste shock ϵ_{ijt}. The strict utility depends on the average utility of a source δ_{jtv} as well as a vector z_{it} of observable household characteristics. These characteristics affect household utility through source-specific coefficients γ_j. For example, households with higher incomes may have a greater preference for grid electricity, but an unchanged preference for diesel.

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

$$\delta_{jtv} = x'_{jtv}\overline{\beta} + \xi_{jtv} \tag{7}$$

The vector x_{jtv} of observable source characteristics includes price, hours of supply on-peak (from five to ten pm) and hours of supply off-peak. We refer to ξ_{jtv} as unobserved quality or just quality. Unobserved quality is known to households but not the econometrician. It may include both unmeasured physical characteristics, such as the capacity of a solar system battery, as well as characteristics of the service, such as the monetary or hassle costs to obtain a connection.

The choice probabilities in the nested logit model take a simple form.[24] Each electricity source j belongs to a nest g. Our main specification of the demand model will use two inside nests, for microgrids and for non-microgrid sources together (the grid, own solar and diesel generators).[25] The parameters σ_g measure the similarity of sources within a nest. The inclusive value of nest g is

$$IV_{igtv} = \ln \sum_{j \in \mathcal{J}_g} e^{V_{ijtv}/(1-\sigma_g)}, \tag{8}$$

which is the expected indirect utility when maximizing utility across sources in nest g. The probability of i choosing a source j in nest g_j is then

$$\Pr(y_{it} = j | z_{it}) = \frac{e^{V_{ijtv}/(1-\sigma_{g_j})}}{e^{IV_{ig_jtv}\sigma_{g_j}} \sum_g e^{IV_{igtv}(1-\sigma_g)}} \tag{9}$$

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

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

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

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.

[25] On *a priori* grounds several possible nesting structures seem plausible. We use this nesting structure because it yields the best model fit out of all possible nesting structures (see Table B12). Under this structure, we can reject the null hypothesis of a multinomial logit model with no correlation between choice-specific utility shocks (Table B12, column 2, LR test p-value $= 0.05$). The choice of nests is not consequential in our setting, however, since alternative nesting structures yield very similar estimates to those from our main specification (Appendix B e, Tables B12 and B13).

b Estimation

We estimate the model in two stages using data from all three surveys. The first, non-linear stage estimates the effects of observable characteristics on household choices (9) via maximum likelihood. The second, linear stage estimates use the mean indirect utilities $\hat{\delta}_{jtv}$ from the first stage as the dependent variable to estimate equation 7 using two-stage least squares. This two-step procedure is common to address endogeneity in the estimation of random coefficients logit models (Berry, Levinsohn and Pakes, 1995, 2004), of which the nested logit is a simple case. The key idea is to invert market shares to solve for mean indirect utilities, which then allows for linear IV estimates in the second stage that are unbiased despite the endogeneity of price to quality (Berry, 1994).

Non-linear estimation of the first stage. In the first stage, we use maximum likelihood to estimate the parameters δ, γ and σ using choice probabilities (9) and indirect utility (5). Let y_{itj} indicate that household i in survey t chose product j. The log-likelihood of the sample is

$$\log \mathcal{L}(\gamma, \sigma | y, z) = \sum_{i=1}^{N} \sum_{t=1}^{T} \log \Pr(y_{itj} | z_{it}; \gamma, \sigma, \delta(\gamma, \sigma)). \tag{10}$$

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.[26] This greatly reduces the dimensionality of the non-linear search, as the δ vector could have up to 1200 elements (= 100 villages $\times$ 3 surveys $\times$ 4 sources), if every source were available in every village.

Linear estimation of the second stage. We can now use equation 7 to recover the $\overline{\beta}$ vector via a linear regression of the estimated $\widehat{\delta}_{jtv}$ on the observable characteristics x_{jtv} of electricity sources at the survey-by-village level. 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. The main concern with estimation of equation 7 is that the error term $\tilde{\xi}_{jtv}$ measures the unobserved quality at the source by survey by village level, inferred from market shares. If a source is very good in a

[26] 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.

particular village at a particular time, for example a diesel operator allows higher loads, then the price of that source may endogenously be set higher, implying $\mathbb{E}[\tilde{\xi}_{jtv}|x_{jtvk}] \neq 0$. Additionally, the price variables are derived from survey reports, so measurement error may attenuate the estimated price coefficient.

The traditional solution to these concerns is to instrument for price or other characteristics that may be endogenous to quality. Our solar microgrid experiment offers instruments that are excludeable and likely to be powerful, given that the microgrid treatment changed market shares (Table 5). We use interactions of the village-level treatment indicators T_v^{Normal} and $T_v^{Subsidized}$ and an indicator $\mathbf{1}\{Endline\}$ for the endline survey wave as instruments for price.

The hours of supply on the grid may also be endogenous. To account for this possibility, in our preferred specification we also instrument the supply hours in a village (both on- and off-peak) using predicted supply hours $\widehat{Peak}_{tv}$ and $\widehat{OPeak}_{tv}$, where the predictions are made using supply hours in nearby villages. We expect that villages nearby in the electricity grid, for example that are served by the same substation, will be similarly affected by the distribution companies' power supply rationing rules. The exclusion restriction is that supply of electricity in nearby villages is not correlated with the determinants of demand in a given village, after conditioning on our rich set of household observables. Appendix A c details the construction of the instrument.

With these instruments, we estimate equation 7 by two stage least squares:

$$\begin{aligned} \widehat{\delta}_{jtv} &= x_{jtv,price}\overline{\beta}_{price} + \sum_{k \neq price} x'_{jtvk}\overline{\beta}_k + \overline{\xi}_{jt} + \tilde{\xi}_{jtv} \qquad (11) \\ x_{jtv,price} &= \pi_1 T_v^{Normal}\mathbf{1}\{Endline\} + \pi_2 T_v^{Subsidized}\mathbf{1}\{Endline\} + \\ &\quad \pi_3\widehat{Peak}_{tv} + \pi_4\widehat{OPeak}_{tv} + \overline{\xi}_{jt} + \nu_{jtv}. \qquad (12) \end{aligned}$$

We specify here the first stage for the price equation only. The $\overline{\xi}_{jt}$ are source-by-wave fixed effects. The first stage, equation 12, uses the experimental treatment assignments, interacted with a dummy for the endline survey, when the experiment was ongoing, as instrumental variables.

As a basis of comparison, we will also report results using ordinary least squares and using traditional price instruments from the industrial organization literature. We have two sets of alternate instruments for source-village-wave prices. First, the average hours of supply and load from the other products in the same village, which will affect source mark-ups and prices under oligopolistic competition (Berry, Levinsohn and Pakes, 1995). Second, the average price for a given source in the nearest three villages where that source is available, which will covary with source price due to common supply shocks (Hausman, 1996; Nevo, 2001).

Having estimated equation 11, the fitted residuals allow us to recover mean unobserved quality

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

With these estimates, we can observe how the quality of electricity sources varies across sources, villages and time, as inferred from households' choices.

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 choice probability for that source averaged over households:

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

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

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

We run counterfactuals by considering an alternative set of choices $\mathcal{J}'$ or by using the estimated coefficients to calculate new $\hat{\delta}_{jvt}$ associated with changed source characteristics. The willingness to pay for a scenario that alters the choice set or choice characteristics is:

$$\widehat{WTP} = -\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{\mathbb{E}}\left[\max_j U_{ijtv} \,\middle|\, \mathcal{J}'\right] - \widehat{\mathbb{E}}\left[\max_j U_{ijtv} \,\middle|\, \mathcal{J}\right]\right) \Big/ \widehat{\overline{\beta}}_{price} \tag{13}$$

The main objects of interest in the counterfactuals are predicted market shares and household willingness to pay.

c Results

This section reports estimates of household demand for electricity sources. The full demand model has 1,031 parameters: 999 source-by-village-by-survey wave mean indirect utility parameters, backed out from the first-stage demand model, 28 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 report the linear estimates of the average effects of source characteristics, from the second stage. Second, we present estimates, from the non-linear first stage, of how household characteristics affect choice probabilities. Third, we present distributions of source quality.

Second stage estimates: Mean effect of source characteristics. We begin with estimates of equation 12, which is the first stage of the linear part (second stage) of the broader model. Appendix Table B4 reports the estimates with several different instrumental variables strategies. Our preferred specification (12) instruments for both price and supply hours. We find that the experimental treatment assignments have a highly statistically significant effect on price (column 2a). The first-stage F-statistic for a test of the null that the instruments do not affect price ranges from 21 to 42, depending on whether we instrument for price and hours simultaneously (column 2a), or only for price (column 1). In addition, our supply instruments strongly predict hours of supply both during peak and off-peak hours (columns 2b and 2c).

Alternative instrument sets lack power to predict price in the first stage. Neither the BLP (F-statistic 0.4) nor Hausman (F-statistic 1.0) instruments have much predictive power for the endogenous price variable. One interpretation of this result is that the assumption of oligopolistic conduct that underlies the BLP instruments is not appropriate in this setting, since sources like own solar are perfectly competitively supplied and the government's objective, in pricing grid electricity, is clearly not to maximize profits.

Table 7 reports estimates of the linear part of the demand model, equation 11. Column 1 reports results from ordinary least squares estimates, as a straw man, since we expect OLS will be biased. Columns 2 and 3 report instrumental variables estimates using the first stage from the experiment, instrumenting either for price or for both price and hours. Columns 4 and 5 replace the experimental variables in the instrument set with alternate instruments for price.

The experimental instrumental variables estimates show a high degree of price sensitivity. We find a coefficient of -1.70 (standard error 0.63) on price (column 2), which is unchanged if we additionally instrument for hours of supply (column 3). The magnitude of the coefficient on price is seven times greater than found in the OLS estimates (column 1), consistent with bias from some combination of endogeneity and measurement error.

Estimates of the price coefficient using alternative instruments drawn from the literature are imprecise. The point estimate with the BLP instruments is half as large as the experimental estimate (column 4) and the point estimate with the Hausman instruments is positive (column 5). We cannot reject the equality of either of these estimates with any of the experimental estimates, the OLS estimates, or a zero coefficient on price. We therefore conclude that the experiment is necessary to recover unbiased and precise estimates of the price coefficient in our setting.

We calculate the price elasticities implied by these coefficients using our preferred, column 3 estimates. (The elasticities also depend on the other parameters of the demand model, including household tastes and quality, that we discuss below.) The aggregate own- and cross-price elasticities by source are shown in Appendix Table B5. The demand elasticity for grid electricity is estimated to be -0.58. We view households as very price sensitive in absolute terms. 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 60) decreases grid market share by 2.9 pp (12% of the average share). Though INR 10 is just enough money to buy two cups of tea or three bananas, raising the grid price by this amount in a month cuts market share by a noticeable 3 pp. Demand is even more elastic for off-grid electricity sources. Diesel, own solar and microgrid solar electricity have large own-price elasticities of -1.83, -1.91 and -1.58, respectively.

We also estimate the effect of supply hours on household mean utility. We find a positive but statistically insignificant effect of peak hours of supply on mean utility and a smaller, negative, and borderline statistically significant coefficient for off-peak hours (Table 7, column 3). Our estimate for the value of peak hours is not precise, but agrees with the idea that agricultural households, who may be away during the day, mainly value power in the evening hours. We proceed with the column 3 estimates, instrumenting for both price and hours, as our main specification for counterfactual analysis. The IV specification is preferred on the *a priori* grounds that supply may be endogenous to village demand.

First stage estimates: Heterogeneity in demand across households. Table 8 reports the effects of household characteristics on choice probabilities from the demand model when estimated across all three periods (the γ_j coefficients on household observables for each source in equation 5). We estimate two instances of the model. First, to provide a simple univariate proxy for wealth, we estimate a model that includes as covariates only the number of adults in the household and a dummy variable for whether the household has a solid roof (columns 1 through 5). Second, we estimate the full model, which includes five additional observable proxies for household demand: whether the household has a solid house, the number of rooms in the house, household income, whether the household owns agricultural land, and the education level of the household head.

The effects of household characteristics are non-linear. The table therefore reports marginal effects evaluated for a "poor" household, which lacks the binary indicators of wealth and has an income at the 20th percentile of our sample distribution.[27] The marginal effects are not strictly marginal; for binary variables we report the effect on each given choice probability of changing the value from zero to one, and for continuous variables the effect of a one standard deviation increase.

The main finding of the table is that richer households, by any measure, have stronger preferences for grid electricity over all other sources. Consider the simple model specification (columns 1 to 5). The baseline probability of grid choice is 24 percent. On top of this base, a household with a solid roof is 21 pp (standard error 3.9 pp) more likely to choose grid electricity. Nearly all of this effect comes from a reduction in the choice of the outside option (no electricity).

In the full model we add additional covariates (columns 6 to 10). The effect of having a solid roof on grid choice declines, since the solid roof dummy is correlated with other measures of wealth, but remains large (11 pp). We find that each of our seven observable demand proxies has a positive, economically meaningful and statistically significant effect on a household's probability of choosing grid electricity, and also reduces the probability that a household chooses no electricity (the outside option). For example, a household that owns agricultural land is 4.9 pp (standard error 1.8 pp) more likely to choose the grid. These demand proxies have much smaller effects on the choice probabilities for other sources, though some do significantly affect demand; for example, higher-income households are slightly more likely to choose microgrids. Table 3 offers a natural interpretation of this heterogeneity: grid electricity supports higher loads, so many more households on the grid can run a fan or a television.[28] Richer households want the energy services that these devices bring. A likelihood ratio test, reported at the bottom of Table 8, easily rejects the simple demand model

[27] The profile of a poor household is defined as a household of two adults living in an one-room house, without a solid roof or solid walls, and no agricultural land ownership. The full profile of a poor household's characteristics is described in Appendix Table B6.

[28] In our baseline survey, very few households reporting using microgrids. As a result, the appliance ownership summary statistics conditional on using microgrids at baseline are imprecisely estimated.

in favor of the full model with additional covariates (p-value < 0.001). We use the full model for counterfactuals.

Unobserved source quality. The demand model flexibly allows for changes in ξ_{jvt}, the mean unobserved quality of each electricity source in each village and survey wave. In the model, unobserved quality is the residual from the estimation of (11). This residual fits the source market shares exactly, conditional on source-specific observable characteristics, and is naturally recovered only for source-village-wave combinations in which the source was available in the market. Quality for a source will be lower if there are unobserved costs of using that source (e.g., connection fees or hassle) and higher if there are unobserved benefits (e.g., reliable service).

Figure 4 summarizes the evolution of source quality. Each row shows one source and each column one survey wave. Within each source and wave, the histogram shows the distribution of quality across villages. We also plot the median source quality as a horizontal line in each histogram.

The main finding from the figure is that we estimate large changes in quality for sources for which we have *a priori* grounds to expect quality improvements, but not otherwise. The two disruptions in the market came from own solar systems and grid electricity. The median quality of own solar improved from -2.6 to -1.2 from 2013 to 2017, with most of the improvement coming in the year between the endline and follow-up survey waves. Higher solar quality may be due to technical factors such as battery capacity and load, which we do not observe directly, or to a broader reach of marketing and distribution networks for these systems, which would have lowered connection costs. The estimated quality of the grid also improved greatly over the span of our data. The median grid quality increases from -1.1 at baseline to -0.3 at endline and $+0.7$ at follow-up (Figure 4, row 1). These improvements are likely the result of a government drive to increase household connections, which decreased connection costs by subsidizing poor households. Quality for diesel generators and solar microgrids, by contrast, stagnated (Figure 4, rows 2 and 3, respectively). The distribution of diesel generator quality is about the same in all three survey waves (though there is truncation at the bottom, due to exit, as generators were driven out of the market). Our microgrid partner, HPS, did not offer its product in many villages at baseline, by design, and did not change its product during our study. This stagnation is apparent in the figure, as the median quality of microgrids is unchanged across survey waves.

Overall, we find a remarkable concordance between our prior understanding of changes in quality for each technology and the unobserved qualities estimated from the demand model. The landscape of electrification in Bihar has shifted, with own solar systems and the grid rapidly improving and other technologies stagnating.

d Modeling choices

The model casts household electricity demand as a static differentiated choice problem. Here we discuss several of our modeling choices.

Nested logit. We use a nested logit model instead of a random coefficients (mixed) logit model for three reasons. First, we have especially rich observable household data that allows for complex patterns of substitution, even without random coefficients.[29] Second, we find that introducing a small amount of unobservable correlation in tastes, via the nested logit assumption, has negligible effects on the estimates.[30] Third, the nested logit model can be estimated efficiently by maximum likelihood without simulation.

Substitutes. The model's structure 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 see very little bundling in our sample, perhaps because households are too poor. At the time of our endline survey, only 1.4% of households held multiple sources (Appendix Table A2). For these few cases, we set a priority order in which households are assumed to have chosen the grid if it is part of their chosen bundle.

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 for on a monthly basis, own solar being the exception, and so households do not have any asset value from holding these sources.

[29]We have household-level panel data with very detailed 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. A mixed logit model would allow patterns of substitution to be richer still. We believe the gains from a more complex model would be larger in settings where one had fewer observable proxies for demand and a larger number of product choices.

[30]Appendix Table B12 shows that the coefficients on observable characteristics and the fit of the model barely change at all when varying the nest structure, or using a multinomial logit model with no nest at all. Nested logit is a simple case of a mixed logit model where the random coefficients are on group-specific dummy variables (Cardell, 1997).

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 period, and massive changes in shares from one year to the next. These fluid aggregate movements suggest that households do not show a stickiness in their connection to a particular source. Our model does allow for unobserved adoption or connection costs, via the quality terms.

4 Competition between Sources and the Value of Electrification

The model estimates now allow us to measure the surplus households gain from electricity and to study how that surplus depends on the competition between different electricity sources. We do this in three steps. First, we use the model to compare the surplus from electrification to the surplus from microgrids alone. Second, we use the model to value the two disruptions that Bihar went through during our study period, the advent of off-grid solar and a big push for grid supply. Third, we study counterfactual policies that project recent shifts in supply and demand forward, to understand the medium-run future of electrification.

a The value of microgrids and of all electricity sources

We start by returning to the estimates of the value of microgrids in Table 6. With the structural model, we can calculate the surplus from any electricity source, by raising the price of that source to a high level and calculating the decline in total surplus (equation 13).

The value of microgrids is nearly the same in the structural model as calculated previously with the linear model of demand. Table 6, panel B, column 4 reports the surplus from microgrids at the time of the endline survey, which we find to be INR 93 per sample household per year. This estimate is very close to the surplus of INR 91 based on a linear estimate of demand (panel B, column 2). It is reassuring that these estimates are similar, given that the experimental variation in price was used to estimate both the reduced-form and the structural demand models.

With the full structural model, we can additionally calculate the surplus from all sources of electricity together. We find that the total household surplus from electrification is INR 528 per year, greater than the surplus from microgrids by a factor of roughly five (Table 6, panel B, column 4 versus column 3). This large difference shows that the modest value of microgrids found in Section 2 does not reflect a low valuation of electricity but rather the availability of other sources of electricity that are similar in appeal to microgrids. Studying demand for microgrids alone, without considering other sources of power, grossly understates household willingness to pay for electricity.

The model estimates show similarly large gaps between the value of electricity and the value of *any* one source of electricity. For example, we repeat the above comparison of source-specific surplus to total surplus from electricity for the grid, instead of for microgrids. We find that the surplus from all sources is greater than the surplus from the grid alone by a factor of roughly three. The grid is unilaterally the highest-quality source at endline (Figure 4, row 1, column 2), but there is a wide scope for substitution between sources of electricity that offer similar energy services, which implies that the value of the source bundle is much greater than for any one source, even the grid.

b The two disruptions in Bihar's electricity market

The substitution we observe between grid and off-grid sources of electricity affects not only our interpretation of the experimental results, on the value of microgrids, but also our understanding of Bihar's larger transformation in electricity access. Here we apply our model to measure the contribution of the two disruptions in Bihar's electricity market, the advent of solar power and the big push of the grid, to the household surplus from electrification.

Table 9 reports a range of counterfactual results based on the demand model estimates. Every row represents one counterfactual model run. Columns 1 through 4 report source market shares and column 5 the electrification rate, the sum of the market shares of all inside sources. Columns 6 to 8 report consumer, producer and total surplus. All surplus measures are per household per year across the entire population, including households who choose the outside option of no electricity. The producer surplus is the surplus from the grid only, which is approximately equal to total producer surplus in the market.[31] Producer surplus is typically negative, because the state distribution company loses money on every grid customer.

Table 9, panel A summarizes the transformation of the electricity market during the span of our

[31] Producer surplus for the grid is a measure of variable profits: the profits or losses that accrue to the state from supplying grid electricity, after accounting for the cost of energy supplied. Losses must be covered by tax collection from Bihar and from other states, due to central government transfers. 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. The assumption of zero profits is probably accurate for own solar but not for diesel, which, in any case, has a small market share at endline.

data. The three rows show the modeled market shares and the value of electrification in each of our three survey waves.[32] In each survey wave, the supply side of the market changes due to changes in source availability, quality and observed source characteristics like price. The demand side of the market changes due to observed household characteristics (except at the follow-up wave, which did not collect household covariates and therefore uses household characteristics at endline).

The main finding in the panel is that the increase in electrification during our study period tripled the household surplus from electricity supply, from INR 309 to INR 935 per household per year (column 6). To put this in context, at baseline, household expenditure on electricity and lighting in our sample was INR 2,029 per year and on all energy INR 6,024 per year. The increase in surplus from electrification is therefore 31% of baseline electricity and lighting expenditures and 10% of all energy expenditures. Grid market share rises by 34 pp (column 1) and the combined market shares of the two solar sources by 15 pp (columns 3 and 4). Even as consumer surplus increases three-fold, producer surplus steeply declines (column 7), as the state loses money on the additional consumers choosing to connect to the extended and improved grid.

In the model, we can decompose household surplus gains into gains due to each of the two large disruptions to the electricity market. Table 9, panel B isolates the value of the disruption from off-grid solar, which includes not only microgrids but also households' own solar systems, relative to the baseline equilibrium. Row 1 repeats a summary of the state of the market at baseline. Row 2 fast forwards solar technology by four years, to the levels of availability, characteristics, pricing and quality at our follow-up survey, holding the rest of the state of the market constant at baseline levels. Row 3 gives the change between these two rows.

The progress of solar power, over only the four years we study, would *alone* have increased household electrification rates by 25 pp (panel B, row 3, column 5) and the household surplus from electrification by INR 358 (panel B, row 3, column 6), or by a factor of 2.2× over the baseline value. The value of only the progress in the category "solar" is more than three times as large as the estimated surplus from microgrids alone, as of the endline survey (Table 6, panel B, row 3).

[32]By construction, the unobserved source quality terms allow the model to fit the actual source market shares almost exactly in each survey wave. There are small differences between source-specific market shares in the model and the data, due to two factors: (i) our use of the Laplace correction in modeling market shares (see footnote 26 above) (ii) the classification of source-level availability at the village-level, which disallows some households in the model from choosing the source they reported in the data (such as microgrids, when microgrids were not offered). See Appendix Table B3 for a discussion of model fit.

Improved solar takes market share from the grid and diesel, and therefore increase solar market shares by 10 pp more than the overall increase in electrification (panel B, row 2 versus row 1).

The value of solar is highly contingent on the state of the grid. Panel B, row 4 repeats the same calculation, of the change in surplus due to better solar, but with the availability, characteristics and quality of the grid at improved follow-up levels, instead of the patchier coverage and supply observed at the baseline. In this case, we find that the change in surplus due to the progress of solar is INR 127 (panel B, row 4, column 6), about one-third as large as if the rest of the market had stood still, and that solar increases the electrification rate by only 8 pp instead of 25 pp. The progress of solar, therefore, is *much* less valuable to households when the government is making large investments to expand a heavily subsidized grid.

An ancillary benefit of solar power is that the government loses less money on grid power supply for every customer that off-grid solar takes off the grid. Panel B, row 4 shows that at the higher, follow-up state of grid availability and quality, the advent of solar power increases producer surplus by INR 129 per household (column 7), by stealing money-losing customers from the grid. This benevolent competition therefore reduces government losses from rural electricity supply by 14% (= 129/928, from panel C, row 2, column 7 over panel B, row 4). This finding provides a novel justification, aside from environmental externalities, for why developing country governments that subsidize the grid may wish to subsidize household solar adoption also.

Table 9, panel C runs a converse set of counterfactuals to isolate the contribution of the expansion and improvement in grid electricity supply to household surplus, with and without improved off-grid solar. Row 1 again repeats the baseline market conditions for reference. Row 2 shows the levels of market shares and surplus with the grid as of our follow-up survey and the rest of the market fixed at baseline. Row 3 shows the changes from baseline due to the improved grid. Row 4 shows the changes from baseline due to the improved grid, if follow-up solar system characteristics are used, instead of their baseline values.

The progress of the grid between 2013 and 2017 would, with the rest of the market frozen at baseline levels, have increased electrification rates by 26 pp and household surplus from electrification by INR 488 (panel C, row 3, columns 5 and 6), a factor of 2.6× over the baseline value. With solar power instead at its improved, follow-up state, the same grid expansion and increases in quality would have increased surplus by INR 257, about half of the increase if only the grid had improved (panel C, row 4). Therefore surplus for the grid, as for solar power, is markedly lower in the presence of viable competing sources of electricity. The value of any source of electricity is not a constant, but depends on the state of the rest of the market.

Using the model to interpret the transformation in Bihar's electricity market, we therefore find that the contribution of off-grid solar power to household surplus from electricity is three-quarters as large as that of the improved grid, when each improvement is considered unilaterally (0.73 = 358/488, panel B, row 3 over panel C, row 3). This near-parity in consumer surplus gains is remarkable, given that solar panels are provided in private markets and the public grid is massively subsidized. The state distribution company's economic model, wherein each added customer increases losses, means that the progress of the grid between baseline and follow-up is projected to *reduce* producer surplus by INR 819 (panel C, row 2, column 7), almost double the gain in consumer surplus. The advent of off-grid solar, by contrast, achieves nearly the same gain in household surplus without this large, offsetting loss.

This characterization of the two disruptions in Bihar speaks to the importance of using the model to look beyond the value of microgrids that we can estimate directly from demand in the experiment. The results from the microgrid experiment are modestly pessimistic about the value of off-grid solar; microgrids could compete, when subsidized, but ultimately lost out in the marketplace. In the larger picture, however, microgrids lost out to a combination of the grid and *other off-grid solar sources.* The demand model allows us to step back and observe that all off-grid solar technologies together contribute nearly as much to the household surplus from electrification as does the grid, without causing any increase in producer losses via state subsidies.

c Counterfactual policy reforms and the future of electrification

What is the future of electrification along the global electrification frontier? This subsection uses the results of the demand model to project the medium-run future of electrification in Bihar. We structure our counterfactuals in order to comment on how electrification will proceed under a range of projected shifts in the market, including further declines in solar prices, improvements in grid extension and service quality, growth in household income and increases in grid prices. We consider a series of counterfactual changes that are large, but realistic, in the dynamic environment of Bihar:

Falling solar prices. Solar panel and battery prices are projected to continue to fall. We use estimates from the literature of a reduction in solar cost of 30% by 2022 (Feldman, Margolis and Denholm, 2016; Howell et al., 2016), and assume that this decline passes through completely to the prices of both own solar systems and microgrids.[33]

Improving grid. As of the follow-up survey, the grid is still only present in 72% of villages and supplies on average 14 hours of power a day, with only about 3 hours during the 5-hour evening peak. The government continued to invest in grid extension and household connections after our surveys and has increased supply to rural areas. We counterfactually complete the extension of the grid to all villages and increase peak supply hours by two hours a day, up to a maximum of five hours, the full duration of the evening peak.

Growing incomes. Bihar is a relatively poor state but among the fastest growing in India, with an average annual growth rate in state product of 11% from 2012 to 2018. To model demand growth, we create profiles that represent "poor," "median" and "rich" households within our sample. These profiles are vectors of household observable characteristics where each element roughly corresponds to the 20th, 50th and 80th percentiles for each wealth and income proxy (see Appendix Table B6 for a description of the profiles). In the counterfactuals, we weakly raise all households to the maximum of their current observables and the median profile, or the maximum of their current observables and the rich profile. These are large relative changes but small in absolute terms; increasing household income to at least the 80th percentile of the distribution in our sample reaches parity only with the per capita GDP of Malawi, one of the world's poorest countries.[34]

Table 9, panel D reports on the results of these counterfactuals. Panel D begins from the state of the market in our follow-up survey, in row 1, and cumulatively adds improvements to the supply and demand sides in the market. Each row below row 1 therefore includes all of the changes up through the prior row.

Further declines in the cost of solar are projected to have moderate effects, increasing the

[33] 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 the panel and batteries only make up a part of the system, these changes imply a reduction in total cost of 30%, or INR 50 (USD 0.83) (See Appendix Figure C4 for a breakdown of costs). We assume that this decline in cost passes through completely to microgrid prices, thereby lowering prices from a market price of INR 170 to INR 120.

[34] The median reported household per capita income in our sample is INR 12000 per year (USD 656 at 2011 PPP) and the 80th percentile is INR 14250 per year (USD 779 at 2011 PPP). At purchasing power parity rates, the 80th percentile in our sample is therefore about in line with per capita income in Malawi (USD 1143 at 2011 PPP) (World Bank). Income measurement is difficult for rural, agricultural households with multiple sources of income, and this comparison should only be taken as roughly indicative of the level of economic development in our sample.

electrification rate by 3 pp and household surplus from electrification by 10% of the follow-up status quo (row 2). Solar market shares increase by nearly four times the net gain in electrification, as cheaper solar draws households away from the grid.

Completing the "big push" of the grid, to reach all villages (row 3) and improve supply (row 4), would increase electrification rates by a further 9 pp (column 5) and surplus by one-quarter of the follow-up status quo (column 6, row 4 compared to row 2, and row 4 compared to row 1 $= (1245 - 1024)/906$). Grid extension contributes somewhat less to this gain than intensive margin improvements in peak supply for all villages (column 6, INR 84 per household, in row 2, versus INR 137, row 3 less row 2). Although the grid improved greatly during the span of our data, the further gains in these counterfactuals show that an incomplete and low quality grid remains a major hindrance to electricity access.

We now take the "big push" on the supply side, including reductions in solar cost and improvements in grid extension and reliability (up through panel D, row 4), as given, and consider the effects of increasing all households' incomes to the median and rich profiles in rows 5 and 6, respectively. Gains in household income have large effects on the value of electrification. In the median (row 5) and rich (row 6) scenarios, the electrification rate surges to 83% and 90%, respectively. Taking the "big push" scenario (row 4) as the point of comparison, increasing household income boosts the surplus from electrification by 49% (= 1859/1245, column 6, row 6 over row 4), or 68% of the total household surplus from electrification as of follow-up (row 1). A striking aspect of these gains is that they are entirely due to the grid—the overall electrification rate increases 13 pp (column 5, row 6 less row 4), while the grid electrification rate increases 16 pp (column 1, row 6 less row 4), 123% of the total. This projected dominance of the grid, in response to income growth, was foreshadowed by our demand model estimates, which showed that moderately richer households, those with a solid roof for example, have *much* stronger preferences for grid electricity.

This result on the dominance of the grid presumes that the state is willing to bear the large additional losses that would occur from a subsidized grid expansion. Producer surplus declines by INR 751 per household due to the "big push" (row 4 less row 2) and a further INR 614 per household due to income growth (row 6 less row 4). By row 6, the government is losing INR 1,909 per household in electricity subsidies, about equal to baseline household expenditures on electricity and lighting. As the grid improves, it is reasonable to expect that the government may at a point limit the growth of subsidies by raising prices. In panel D, row 7, we consider a scenario where all of the changes up to row 6 still occur, but the government also raises prices, in order to limit producer losses to the follow-up level (column 7, row 1). We calculate that holding losses steady would require a price increase from INR 60 to INR 115.

The results of this scenario shift nearly all of the forecasted gains in electrification off the grid in favor of off-grid solar. The overall electrification rate falls only 6 pp (column 5, row 7 less row 6). The *grid* electrification rate, however, falls 29 pp (column 1), and the solar rate surges 22 pp. At prices closer to cost recovery, solar power would continue to play a much larger role in electrification, even as the extent and quality of the grid improves.

The comparison of these scenarios, particularly the contrast of row 6 and row 7, makes it clear that the future of electrification is a social choice. If the government makes a big push and retains the present level of subsidies as household income grows, nearly all of the gains from household electrification will come from the grid. If subsidies are withdrawn to hold the line on the budget, then off-grid solar power will continue to play a large role in the electrification of the poor, nearly coequal with that of the grid.

5 Conclusion

Electricity markets on the global electrification frontier are undergoing radical changes, driven by innovation in solar power and a traditional "big push" for grid electricity. We model the demand for *all sources* of electricity and apply the model to break down the gains to the poor from a large expansion of energy access. Our approach uses revealed preference measures of demand, estimated with medium-run experimental variation, to value historic changes in energy supply, which would not have been feasible directly to manipulate with an experiment. As a point of comparison, the increase in electrification rates within our four-year study period is roughly twice as large as the increase in farm electrification rates studied by Kitchens and Fishback (2015), who consider a decade of gains from the beginning of the Rural Electrification Administration in the United States.

There are three main findings from our analysis of the electricity market over a dynamic four-year period in rural Bihar. First, the household surplus from electrification tripled during our study period. Second, while households value electricity, no single source is indispensable, since households freely substitute between several sources that provide similar energy services at similar prices. Both the advent of solar power and the big push of the grid would, on their own, have more than doubled the household surplus from electrification, with the grid playing only a modestly larger role. Third, future gains in electrification will come mainly through the grid, because households prefer the grid even at a strikingly low level of economic development. This finding depends on Bihar's policy regime; the pace of the transition to the grid, in general, will depend on whether energy subsidies keep pace with demand.

We omit at least two valid reasons why governments may favor energy subsidies for the poor. First, a preference for redistribution. The large loss that Bihar is willing to incur to increase electrification rates is one measure of the value that the state places on energy access *per se*. A drawback of redistribution through energy subsidies is that subsidies, ironically, can undercut the quality of energy supply (Burgess et al., 2020; Dzansi et al., 2019). A pullback in supply, in turn, may slow economic growth, for example the growth of manufacturing firms (Allcott, Collard-Wexler and O'Connell, 2016). The second factor that favors subsidies, for the grid in particular, is external returns, for example a big push for electrification might generate spillovers in consumption or increases in productivity for firms, beyond the direct value of electricity to consumers. The evidence on external returns is uncertain and more research in this area is needed (Lipscomb, Mobarak and Barham, 2013; Kline and Moretti, 2014). Governments in pursuit of such returns may reasonably push for universal electrification, even if it may seem *too early* in the process of development, as measured by household willingness-to-pay alone. Indeed, Bihar's big push has come at a very low level of income, relative to historical precedent (Lee, Miguel and Wolfram, 2020*a*).

The expansion of the electricity choice set that we study has brought a large increase in household surplus from electrification in a short time. Off-grid solar is not leaping over the grid, as mobile telephony made the landline obsolete, before landline networks were ever completed. However, it is a worthy competitor for the needs of the rural poor, which has accelerated growth in energy access. Universal electrification is a landmark in the development of every country, but the number of people without grid electricity today is only a bit lower than the world population in 1879, when Thomas Edison invented the light bulb. The pace of change we now observe, both on the grid and off, is not unique to Bihar. Soon enough the global electrification frontier may disappear.

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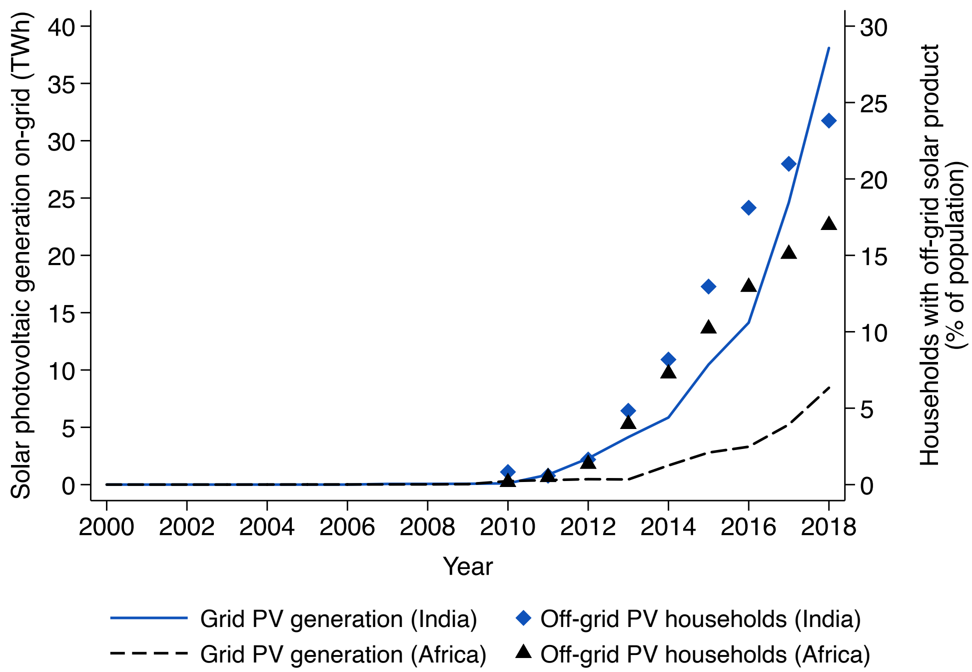
6 Figures

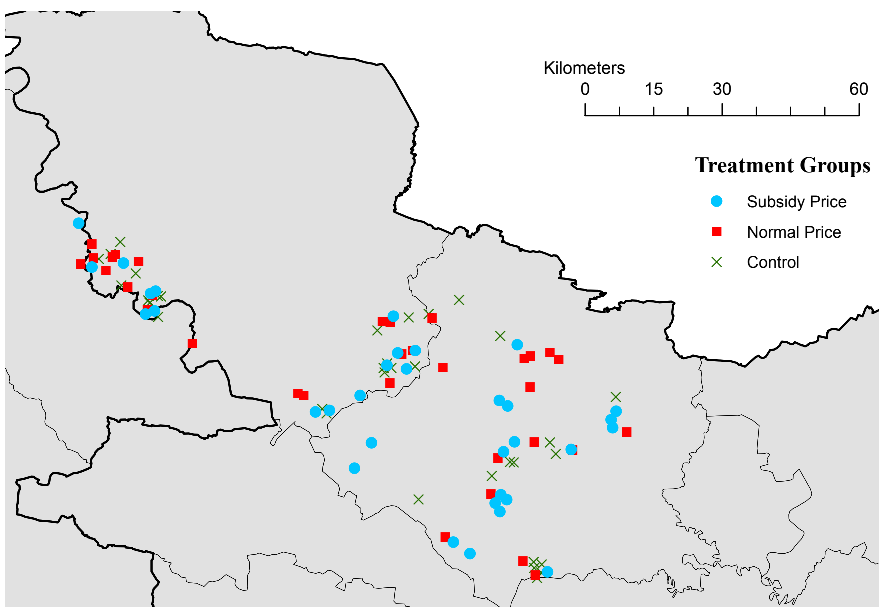
Figure 1: Growth of Solar Power in Developing Countries



The figure shows the growth of solar power in India and Africa, which account for most of the global population without electricity. The line series, measured against the left axis, show grid electricity generation from solar photovoltaics for India and the African continent. Generation data comes from the International Energy Agency, IRENA and the Central Electricity Authority, Government of India. The marker series, measured against the right axis, denote the percentage of households using off-grid solar systems in India and Africa. We estimate cumulative household market shares using data on solar system sales from GOGLA. To calculate the stock of market shares from flow data on sales, we assume that each household owns only one system and the number of systems in use is the sum of systems sold less a 10% annual depreciation of the prior stock. We divide by the population of households using population and household size data from the UN Population Division, the World Bank and the Indian Census.

Figure 2: Maps of Study Area

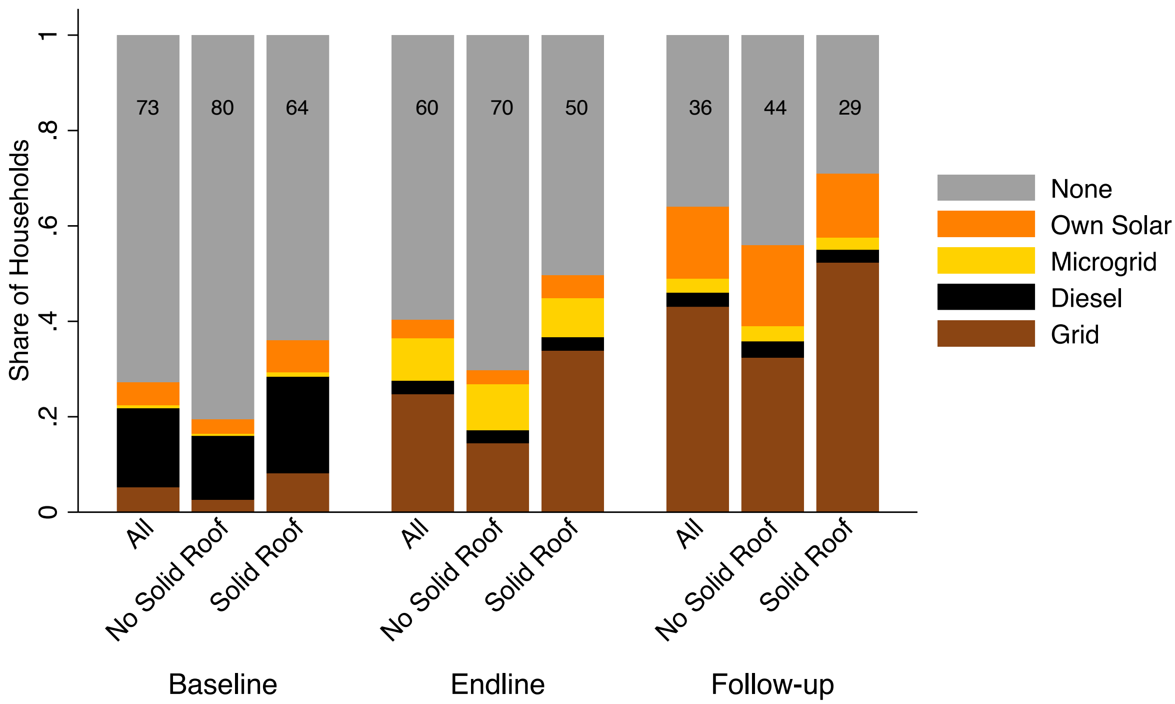
A Study districts within the state of Bihar, India



B Sample villages within study districts

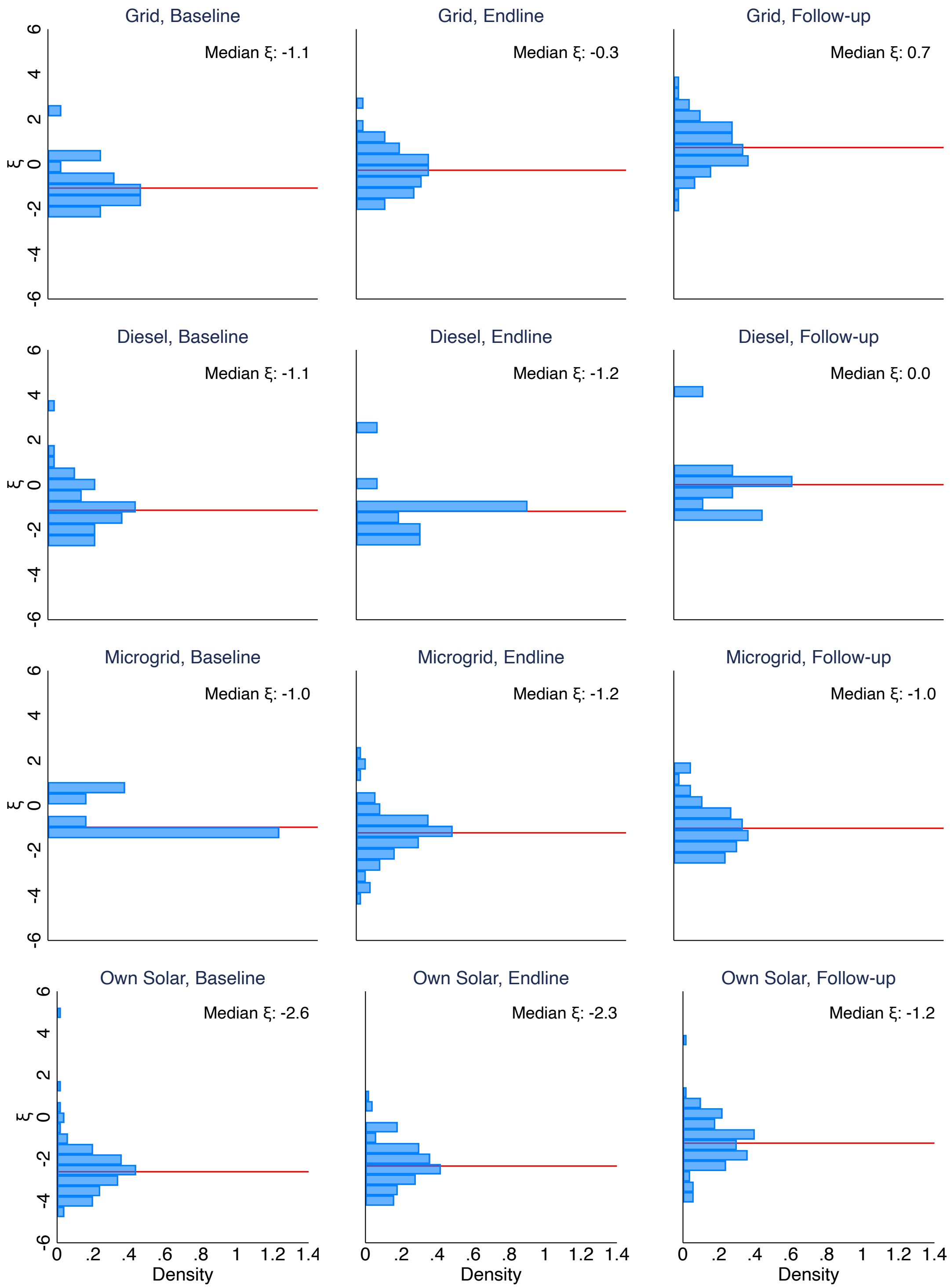
The figure shows the study area. Panel A highlights the two districts of West Champaran and East Champaran, in the northwest corner of Bihar, which contain the study villages. Panel B shows, within the two study districts, the locations of sample villages and their treatment assignments. The nearest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

Figure 3: Household Electricity Sources Over Time



The figure shows the market shares of different sources of electricity over time. Each stacked bar gives the share of households, from bottom to top, that use grid electricity, diesel generators, solar microgrids, own solar systems or no electricity. These market shares are calculated with respect to the total sample of households, without regard for whether a source is available in a village or not; in a village where the grid is not present, for example, the grid necessarily has a zero share. There are three clusters of bars, for shares in the baseline (starting November 2013), endline (starting May 2016) and follow-up (starting May 2017) survey waves. We use a dummy variable for whether a household has a solid roof as a proxy for household assets. Within each cluster of bars, the three bars from left to right give the market shares amongst all households, households that do not have a solid roof, and households that do have a solid roof, respectively.

Figure 4: Evolution of Electricity Supply Quality by Source



The figure plots the estimated distributions of unobserved source quality for all electricity sources over time. The four rows are for different electricity sources, from top to bottom: grid electricity, diesel, solar microgrids, and own solar systems. The three columns are for the survey waves, from left to right: baseline (starting November 2013), endline (starting May 2016) and follow-up (starting May 2017). Each histogram in the figure shows the distribution across villages v of unobserved mean quality $\widehat{\xi}_{jtv}$ for the row source j during the column survey wave t. 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. 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.

7 Tables

Table 1: Grid Electrification Around the World, 2012

	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 (World Bank, 2017).

Table 2: Description of Electricity Sources in Bihar

	Grid electricity (1)	Microgrid solar (2)	Own solar (3)	Diesel generator (4)	No electricity (use kerosene) (5)
Availability	Grid must reach village. Then household can apply for a connection.	Offered in treatment villages by Husk Power Systems.	Available in market towns. Households travel to buy on their own.	Private operators offer in villages with high enough demand.	Sold through Public Distribution System.
Energy services typically supported	Light and phone charging, fans, televisions. No load limit.	Light and phone charging.	Light and phone charging. Fans for larger systems.	Light and phone charging.	Light, of lower quality.
Reliability	Poor. Frequent power cuts at peak times.	Good, but limited by battery capacity.	Good, but limited by battery capacity.	Good, but operates during peak evening hours only.	Good.
Contract	Pay monthly bill, either flat or per unit.	Pay monthly flat bill.	Buy system up-front. Low marginal cost but household liable for maintenance.	Pay monthly flat bill.	Pay by quantity at a subsidized rate.
Risk of disconnection	Disconnection possible, though unlikely, if no payment.	Disconnection possible if no payment.	Not applicable.	Disconnection likely if no payment.	Not applicable.

The table describes the electricity sources that are used by households in our sample in Bihar.

Table 3: Summary of Electricity Sources

	Baseline					Endline					Follow-up				
	Grid	Diesel	Own solar	Micro-grid	None	Grid	Diesel	Own solar	Micro-grid	None	Grid	Diesel	Own solar	Micro-grid	None
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A. Source characteristics															
Price (INR per month)	72	99	80	200	-	60	88	91	164	-	59	89	72	170	-
Load (watts)	322	134	247	31	-	145	22	39	31	-	147	40	13	31	-
Hours of supply															
Total	10.9	3.4	7.4	5.3	-	11.0	3.1	5.6	5.6	-	13.6	3.1	5.6	5.6	-
Peak (5 - 10 pm)	2.0	3.4	4.7	4.3	-	2.1	3.1	4.9	5.0	-	2.8	3.1	4.9	5.0	-
Off-peak	8.6	0.0	2.7	1.0	-	8.8	0.0	0.7	0.6	-	10.4	0.0	0.7	0.6	-
Source in village (%)	29	57	100	0	-	53	18	100	66	-	72	13	100	66	-
Panel B. Household appliance ownership															
Fan (%)	22	2	1	0	0	34	4	9	3	1	-	-	-	-	-
Light bulb (%)	84	93	72	55	2	100	100	99	66	1	-	-	-	-	-
Mobile phone (%)	87	89	97	90	74	95	95	97	92	86	-	-	-	-	-
Television (%)	15	3	10	15	1	11	1	4	2	0	-	-	-	-	-

The table summarizes the characteristics of electricity sources available in our sample. The overarching column headers show each electricity source in each survey wave: baseline (starting November 2013), endline (starting May 2016) and follow-up (starting May 2017). The individual columns then indicate each electricity source. Panel A shows source attributes weighted by sample size at the village level. Price shown is the average monthly price for each electricity source; for grid, the price takes theft into account by multiplying reported payment by the percentage of households that actually pay. Load is imputed based on what appliances the households say they have plugged in. Hours of supply refers to hours per day of electricity supply; for grid, supply comes from administrative data and for the non-grid sources, supply comes from the respective household survey. The final row in Panel A shows the percent of villages where the given source is available. Panel B shows the share of households that own the most popular appliances. Appliance ownership at the follow-up survey is not available, as we did not collect these variables during this thin round of survey.

Table 4: Household Characteristics and Experimental Balance

	Control (1)	Normal (2)	Subsidy (3)	N - C (4)	S - C (5)	F-Test (6)
Panel A. Demographics						
Education of household head (1-8)	2.41	2.67	2.58	0.26*	0.17	1.48
	[2.03]	[2.14]	[2.09]	(0.15)	(0.15)	(0.23)
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)
Panel B. Wealth proxies						
Household income (INR '000s/month)	7.46	7.32	7.28	-0.14	-0.18	0.068
	[6.88]	[6.86]	[7.03]	(0.56)	(0.50)	(0.93)
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)
Solid house (=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)
Owns ag. land (=1)	0.67	0.69	0.67	0.015	0.0022	0.045
	[0.47]	[0.46]	[0.47]	(0.056)	(0.053)	(0.96)
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)
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)
Uses grid (=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)
Uses diesel (=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)
Uses own solar (=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)
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)
Observations	1052	983	1001			

The table reports the balance of covariates in our baseline survey across treatment 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 treatment 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. The final column shows the F-stat and p-value from a test of the null that the treatment dummies are jointly zero at baseline. The rightmost 3 columns have standard errors clustered at the village-level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Solar Microgrid Demand

	ITT Estimates			IV Estimates	
Survey wave:	Baseline	Endline	Follow-up	Endline	Endline
Dependent variable:	Share	Share	Share	Share	log(Share)
	(1)	(2)	(3)	(4)	(5)
Treatment: Subsidized price	-0.001	0.193***	0.081***		
	(0.005)	(0.049)	(0.027)		
Treatment: Normal price	0.009	0.060**	0.020*		
	(0.010)	(0.028)	(0.012)		
Price (INR '00s)				-0.129**	
				(0.052)	
log(Price)					-0.997***
					(0.386)
Constant	0.006	0.023***	0.002	0.347***	-2.079***
	(0.004)	(0.005)	(0.002)	(0.091)	(0.189)
Observations	100	100	100	66	66
First-stage F-Stat				676	1107

The table shows estimates of microgrid demand. The dependent variable in the first 3 columns is the village-level market share of microgrid solar. The independent variables are the subsidized price arm (microgrids offered at INR 100) and a normal price arm (microgrids offered at the prevailing price of INR 200, later cut to INR 160 in some villages). The control arm (microgrids not offered) is omitted. Each column measures market share at one of the three survey waves. Columns 4 and 5 show instrumental variables estimates of the demand curve using linear and log-log specifications, respectively. We instrument for price using a dummy for the subsidized treatment arm. Standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Consumer Surplus from Microgrids versus All Sources of Electricity

	Reduced-form IV Estimates		Structural Estimates	
	Linear	Log-log	Microgrids only	All sources
	(1)	(2)	(3)	(4)
Panel A. Evaluated at microgrid price of INR 100				
Market share	22	13	23	23
Surplus per sample household	222	242	215	645
Panel B. Evaluated at endline prices for microgrids				
Market share	11	6	10	10
Surplus per sample household	91	129	93	528

The table compares estimates of consumer surplus from microgrids to the surplus from all electricity sources. Columns 1 and 2 give estimates of the surplus from microgrids using the reduced-form IV demand estimates of Table 5. Columns 3 and 4 give surplus estimates from our full structural demand model, presented in Table 7 column 3 and Table 8 columns 6 through 10. Column 3 is the change in surplus, in the full demand model, if microgrids are removed from the market. Column 4 is the consumer surplus from all sources of electricity.

Table 7: Demand for Electricity: Estimates of Linear Stage

	OLS	Price IV	Price & Hours IV		
		RCT	RCT	BLP	Hausman
	(1)	(2)	(3)	(4)	(5)
Price (INR 100 per month)	-0.25**	-1.70***	-1.70***	-0.93	10.1
	(0.12)	(0.63)	(0.63)	(5.80)	(22.6)
Hours of peak supply	0.20	0.11	0.21	0.25	0.74
	(0.21)	(0.21)	(0.27)	(0.32)	(1.19)
Hours of off-peak supply	-0.092*	-0.078*	-0.11*	-0.12	-0.21
	(0.047)	(0.046)	(0.058)	(0.074)	(0.23)
ξ_{tj} mean effects	Yes	Yes	Yes	Yes	Yes
Observations	999	999	999	945	989
First-stage F-Stat		42.1	21.1	0.4	0.5

The table presents estimates of the second, linear stage of our demand system (equation 11). The dependent variable is mean indirect utility at the market-by-survey wave level, estimated in the non-linear first stage. Peak hours refers to electricity supply during the evening, from 5 to 10 pm, and off-peak to other hours of the day. The columns estimate the same equation either by ordinary least squares (column 1) or instrumental variables (columns 2 to 5). Each column uses a different set of instruments. In column 2, we use the experimental treatment assignments interacted with a dummy for the endline survey as instruments (equation 12). In column 3, we additionally instrument for hours of supply, on-peak and off-peak, using the predicted hours of supply based on supply in nearby villages. In columns 4 and 5 we replace the experimental instruments with instruments from the industrial organization literature (Berry, Levinsohn and Pakes, 1995; Nevo, 2001; Hausman, 1996). Column 4 uses the average characteristics of the other products available in a given village as instruments (Berry, Levinsohn and Pakes, 1995). The characteristics we use are hours of supply and load. Column 5 uses the average price of each product in the nearest three villages as instrument for its price in a given village (Nevo, 2001; Hausman, 1996). All regressions control for wave-by-source fixed effects. The final row of the table reports the first-stage F-statistic from the price equation. Standard errors are clustered at the village-level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Electricity Source Choice Probabilities by Household Characteristics

	Simple Model					Full Model				
	Grid	Diesel	Own Solar	Micro-grid	None	Grid	Diesel	Own Solar	Micro-grid	None
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Number of adults	0.054	0.008	0.006	0.012	-0.081	0.036	0.002	0.001	0.005	-0.045
	(0.010)	(0.008)	(0.005)	(0.006)	(0.008)	(0.009)	(0.006)	(0.002)	(0.004)	(0.008)
Solid roof (=1)	0.195	-0.010	0.007	-0.009	-0.183	0.107	-0.007	0.005	-0.007	-0.098
	(0.020)	(0.011)	(0.008)	(0.007)	(0.015)	(0.020)	(0.010)	(0.006)	(0.007)	(0.018)
Solid house (=1)						0.077	-0.004	-0.002	-0.005	-0.066
						(0.020)	(0.011)	(0.003)	(0.008)	(0.018)
Number of rooms						0.026	0.011	0.003	0.003	-0.043
						(0.009)	(0.006)	(0.003)	(0.004)	(0.008)
Owns ag. land (=1)						0.049	-0.023	0.003	0.008	-0.036
						(0.016)	(0.009)	(0.004)	(0.009)	(0.016)
Education of household head (1-8)						0.026	0.008	-0.001	0.002	-0.036
						(0.007)	(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)
Observations			8822					8822		
Log-likelihood			-5884.7					-5791.4		
LR index			0.031					0.047		
LR test statistic (p-value)								186.6 (0.000)		

The table shows the effects of household characteristics on the probability of a household choosing a given electricity source. The table reports the results of two models. A simple model, reported in columns 1 through 5, includes as covariates the number of adults in the household and a dummy variable for whether the household has a solid roof. Our full model, reported in columns 6 through 10, includes five additional observable proxies for household demand: whether the household has a solid house, the number of rooms in the house, household income, whether the household owns agricultural land, and years of education of the household head. The effects of household characteristics are nonlinear. The table therefore reports "marginal" effects evaluated for a "poor" household, lacking the binary indicators of wealth and with an income at the 20th percentile. The profile of a poor household is defined as a household of two adults living in an one-room house, without a solid roof or walls, and lacking agricultural land ownership. See Appendix Table B6 for the characteristics of a poor household. The marginal effects are not truly marginal; for binary variables, we report the effect on choice probability of changing the value from zero to one, and for continuous variables the effect of an one standard deviation increase in that variable. To assess the goodness-of-fit of each model, we report a likelihood ratio index, which is defined as $\rho = 1 - \mathrm{LL}(\hat{\beta})/\mathrm{LL}(0)$, where $\mathrm{LL}(\hat{\beta})$ is the log-likelihood at the estimated parameters and $\mathrm{LL}(0)$ is the log-likelihood of a null model, where we constrain all the household characteristic coefficients to be zero. We also report the maximized value of the log-likelihood for both models and a likelihood ratio test statistic, distributed χ^2 with 20 degrees of freedom, from a test of the restriction that the coefficients on the covariates added in the full model are jointly zero.

Table 9: The Value of Electrification under Counterfactual Policies

	Market shares					Surplus (INR per hh per year)		
	Grid (1)	Diesel (2)	Own solar (3)	Micro-grid (4)	All (5)	Consumer (6)	Producer (7)	Total (8)
Panel A. Model market shares and surplus by survey wave								
1. Model at baseline	6	17	7	0	30	309	-109	200
2. Model at endline	24	3	7	9	43	520	-501	19
3. Model at follow-up	41	3	17	4	65	935	-850	86
Panel B. Disruption due to the improvement of solar power, relative to baseline								
1. Market at baseline	6	17	7	0	30	309	-109	200
2. + Improved solar	3	10	37	6	55	667	-53	614
3. Change due to improved solar	-3	-7	29	6	25	358	56	415
4. Change due to improved solar, if grid improved	-6	-2	12	4	8	127	129	256
Panel C. Disruption due to the improvement of grid electricity, relative to baseline								
1. Market at baseline	6	17	7	0	30	309	-109	200
2. + Improved grid	44	9	3	0	56	797	-928	-131
3. Change due to improved grid	39	-8	-5	0	26	488	-819	-331
4. Change due to improved grid, if solar improved	35	-3	-21	-1	9	257	-746	-490
Panel D. Future growth in electrification via supply and demand shifts, relative to follow-up								
1. Market at follow-up	41	3	17	4	65	935	-850	86
2. + Solar cost falls	35	2	24	8	68	1024	-730	295
3. + Grid in all villages	46	2	18	7	73	1108	-960	148
4. + Increase peak grid hours	57	1	13	6	77	1245	-1481	-236
5. + All households at least median income	63	1	14	5	83	1444	-1637	-193
6. + All households at least 80th percentile	73	1	11	4	90	1859	-1909	-51
7. + Raise grid price to hold losses constant	44	2	30	7	84	1456	-850	606

The table presents market shares and surplus under counterfactual changes in the electricity market. The counterfactual scenarios are laid out in Section 4 of the text and the detailed assumptions behind the counterfactuals are in Appendix Table C14. All counterfactuals are calculated using the full demand model estimates of Table 8, columns 6 through 10. For each counterfactual, columns 1 to 4 give the market shares of each source, column 5 gives the electrification share, and columns 6 through 8 give consumer, producer and total surplus. Consumer surplus is the amount in INR per household per year that households would be willing to pay for a given choice set, relative to having only the outside option of no electricity. The amounts of both consumer and producer surplus are averaged over the entire sample of consumers, regardless of their choice. Producer surplus is the variable profit of the state utility that provides grid electricity. Levels rows are unindented, whereas changes rows (where the numbers displayed are differences in two counterfactual scenarios) are indented.

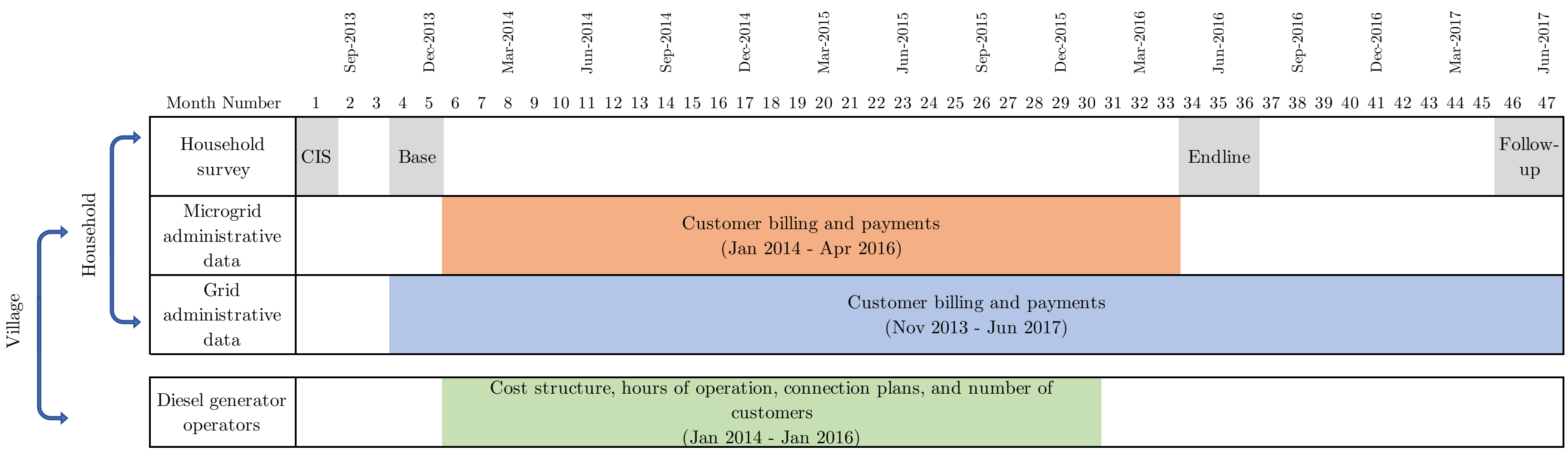
A Appendix: Data

This Appendix describes our data collection and the construction of instrumental variables for hours of electricity supply. We also provide additional summary statistics.

a Sampling and timeline

Figure A1 shows the timeline for the implementation of the experiment and the timing of the data collection. The microgrid experiment ran for roughly 2.5 years but the data collection spanning the experiment covered roughly 4 years in total.

Figure A1: Data Collection Timeline



The figure shows the collection of data during the study from several sources: a household survey, microgrid administrative data, grid administrative data and a diesel operator survey. See Section 1 a for a detailed description of the data sources. In August 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 sampling frame for our household sample. The experiment ran from January 2014, after the conclusion of the baseline survey, through the endline survey in mid-2016.

We describe our panel survey in Section 1 a. We also draw on three other original data sources, which are described below.

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 experimentally in the sample villages (see Section 2). The dataset includes enrollment, pricing and customer payments from January 2014 to January 2016, which we match with our household surveys. This matching allows us to estimate demand in administrative payments data, to complement our survey-based estimates.

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 to the administrative database, as there are high rates of informal connections, i.e. electricity theft, in Bihar. We can measure informal connections by designating households informal if they could not provide a customer ID from their electricity bill, or the ID provided did not match the utility's billing database.

Survey of diesel generator operators. Our final source of data is a survey of diesel generator operators. Entrepreneurs set-up diesel generators and connect 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.

These sources of data allow us to see, on the demand side, a rich set of household characteristics and the sources and uses of electricity. On the supply side, we have data on all the competing sources in the marketplace, in some cases from both administrative sources and our household and operator surveys.

b Construction of hours of supply for grid

The household survey provides most of the characteristics of sources that we use in our demand model. An exception is the grid hours of supply, which we obtained from administrative logbooks maintained by the North Bihar Power Distribution Company Limited. The logbooks record the hours when the grid is switched on and off at the level of the feeder, the lowest level of the distribution network at which the company exercises control over power supply. We aggregated this data from the hourly level to compute average daily hours of electricity supply to each feeder, both on-peak (from 5 to 10 pm) and off-peak. We then mapped our 100 sample villages to their respective supply feeders.

Some villages were missing data around the time of our endline survey. If a village was missing data during the endline survey, we imputed hours of supply with the hours of supply data for that same village within a window running from 6 months before to 6 months after the survey. If the village had no data in that window, we imputed hours of supply data based on the hours of supply for the three nearest villages for which we had data, using a random forest model. The model additionally included as covariates latitude and longitude, division fixed effects and their interactions. The root mean squared error of our prediction, for villages where data is available, is 1.9 hours.

c Construction of instrument for hours of supply

The experiment provides instruments for price but not for other product characteristics, which in principle may also be endogenous to demand: for example, a high-demand village may be given more supply by the distribution company. Our preferred specification for the second-stage linear IV estimation therefore instruments for price, peak, and off-peak hours of electricity supply.

The instruments for peak and off-peak hours of supply are the predicted peak and off-peak hours of supply for a given village based upon hours of supply to nearby villages, as described in Appendix Section b above. We expect hours of supply to nearby villages to be correlated since they are served by the same feeders or by separate feeders from the same substation, which would experience correlated supply shocks such as for rationing decisions.

For non-grid sources we set predicted hours of supply based on their technological characteristics. We set off-peak hours for diesel and microgrid solar to be zero, and assume that all supply is on peak. For own solar, we set peak and off-peak supply to be constant and equal to the global mean of each variable. In this way, there is no variation in predicted supply for off-grid sources and so the variation to identify the coefficients on supply hours come solely from variation in predicted supply for grid electricity.

d Summary statistics

Appendix Table A1 shows comparisons of household characteristics by the timing of grid arrival in a given village. We divide villages into three groups: "grid early" villages already had the grid at the time of our baseline survey, "grid late" villages got the grid by the time of our follow-up surey, and "no grid" villages did not get the grid at any time during our data collection.

The table compares household characteristics, at baseline, across these several sets of villages. The first three columns show mean household characteristics for household in each group of villages. Columns 4 and 5 test for differences in means between "grid early" and "no grid" and "grid late" and "no grid" villages, respectively. Column 5 gives an F-test for the joint equality of means across all three groups.

Table A1: Household Characteristics and Experimental Balance By Grid Access

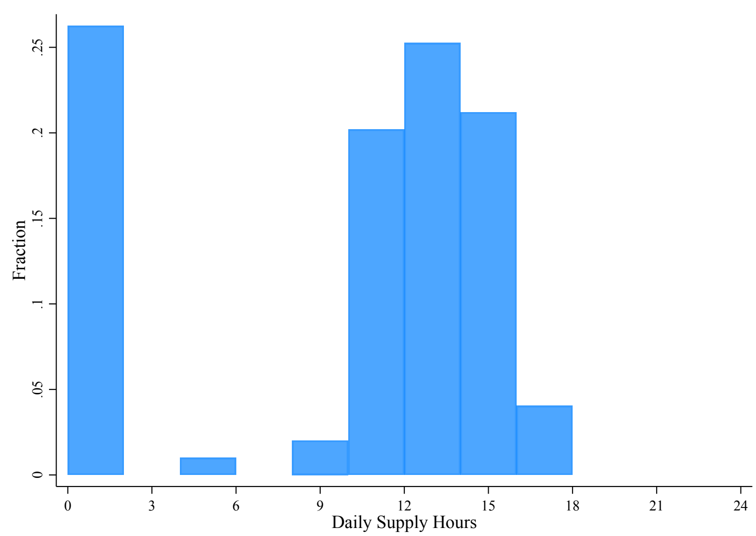
	No grid (1)	Grid early (2)	Grid late (3)	Early - No (4)	Late - No (5)	F-Test (6)
Panel A. Demographics						
Education of household head (1-8)	2.20	2.78	2.55	0.58***	0.35**	8.41***
	[1.80]	[2.25]	[2.07]	(0.14)	(0.14)	(0.00)
Number of adults	3.46	3.44	3.41	-0.022	-0.052	0.098
	[1.69]	[1.67]	[1.73]	(0.11)	(0.12)	(0.91)
Panel B. Wealth proxies						
Household income (INR '000s/month)	6.92	7.28	7.66	0.36	0.74	0.92
	[6.26]	[6.52]	[7.56]	(0.51)	(0.55)	(0.40)
Number of rooms	2.45	2.51	2.50	0.056	0.043	0.18
	[1.25]	[1.49]	[1.42]	(0.099)	(0.098)	(0.83)
Solid house (=1)	0.16	0.33	0.29	0.16***	0.12***	16.6***
	[0.37]	[0.47]	[0.45]	(0.029)	(0.031)	(0.00)
Owns ag. land (=1)	0.80	0.62	0.66	-0.18***	-0.13***	9.96***
	[0.40]	[0.49]	[0.47]	(0.046)	(0.042)	(0.00)
Solid roof (=1)	0.32	0.55	0.47	0.23***	0.15***	18.7***
	[0.47]	[0.50]	[0.50]	(0.038)	(0.042)	(0.00)
Panel C. Energy access						
Any elec source (=1)	0.15	0.34	0.28	0.20***	0.13***	9.30***
	[0.36]	[0.48]	[0.45]	(0.047)	(0.048)	(0.00)
Uses grid (=1)	0	0.15	0	0.15***	0	51.4***
	[0]	[0.35]	[0]	(0.021)	(0)	(0.00)
Uses diesel (=1)	0.082	0.15	0.23	0.067	0.14***	4.57**
	[0.27]	[0.36]	[0.42]	(0.045)	(0.049)	(0.01)
Uses own solar (=1)	0.055	0.038	0.052	-0.017	-0.0029	0.69
	[0.23]	[0.19]	[0.22]	(0.016)	(0.016)	(0.50)
Uses microgrid solar (=1)	0.011	0.0093	0.0016	-0.0020	-0.0098	1.72
	[0.11]	[0.096]	[0.040]	(0.0092)	(0.0072)	(0.18)
Observations	705	1071	1260			

The table reports the balance of covariates in our baseline survey by timing of grid arrival 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 for villages that never receive grid access during our survey data collection, receive grid access during our baseline survey and receive grid access during our endline or follow-up survey, with standard deviations in brackets. The next two columns show the differences between the early grid and never grid groups and late grid and never grid groups, respectively. The final column shows the F-stat and p-value from a test of the null that the grid access dummies are jointly zero at baseline. The rightmost 3 columns have standard errors clustered at the village level and shown in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

The table shows that villages that got the grid earlier are significantly richer than villages that got it later. In villages that got the grid earlier, households are twice as likely to have a solid house, more likely to have a solid roof and have more educated household heads. Households in early villages are also *less* likely to own agricultural land, suggesting they may have non-agricultural occupations at higher rates. Finally, households in grid early villages have higher access to electricity, from any source, at baseline. This effect is not purely a mechanical effect due to grid presence but may reflect underlying differences in household demand. For example, "grid late" villages, which did not have the grid at the time of our baseline survey, nonetheless have greater electricity access at baseline than "no grid" villages, but this higher access is provided by diesel generators and not the grid itself.

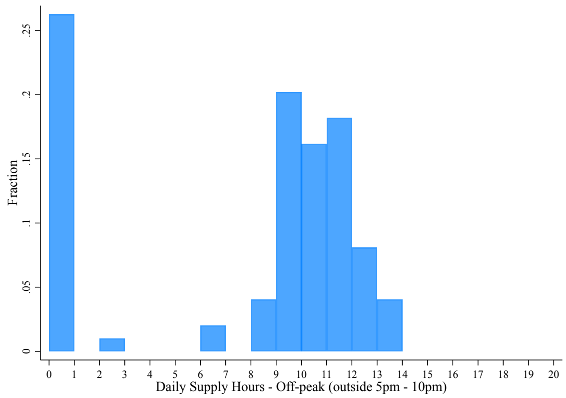
Appendix Figure A2 shows the distribution of daily hours of electricity supply on the grid and Figure A3 the distributions of supply hours during off-peak and on-peak times. Appendix Table A2 shows the market shares of electricity sources at endline accounting for the possibility of ownership of multiple sources.

Figure A2: Daily Hours of Supply on the Grid

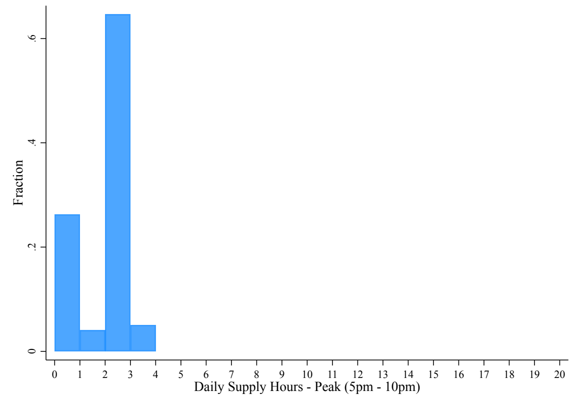


This figure shows the distribution of the daily average hours of grid electricity supply across villages in our sample at the endline survey.

Figure A3: Hours of grid supply off-peak and on-peak



A Off-peak supply



B Peak supply

The figure shows the distribution of grid hours of supply. The data come from administrative logbooks of hourly supply to sample villages. Panel A shows the distribution of hours of supply during the off-peak period and Panel B during the peak period of 5 to 10 pm. The maximal possible hours of supply in the peak period is therefore 5 hours and during the complementary off-peak period 19 hours.

Table A2: Electricity Source Ownership at Endline

	Frequency (1)	Percentage (2)	Cumulative Percentage (3)
Grid	681	22.43	22.43
Diesel	81	2.67	25.10
Own solar	148	4.87	29.97
Microgrid	141	4.64	34.62
Grid & Own solar	28	0.92	35.54
Grid & Microgrid	14	0.46	36.00
None	1824	60.08	96.08
No data	119	3.92	100.00
Total	3036	100.00	100.00

This table shows the household level take-up rate for different electricity sources, accounting for joint ownership, at the endline survey.

B Appendix: Additional Results on Demand

This section presents additional results on demand. Subsection a reconciles market shares in the raw data, with Laplace correction, and as predicted by our structural model. Subsection b presents estimates of the first stage from the estimation of the second, linear part of our structural demand model. Subsection d gives the profiles of households, which are used to calculate marginal effects in the demand model, and shows the heterogeneity of the estimated marginal effects by household profile. Subsection e provides additional estimates to check the robustness of the structural demand estimates to alternative nest structures in the nested logit model.

a Market shares: model versus data

Table B3 presents the fit of market shares in the model to the data by survey wave and electricity source. In principle the model can fit the data exactly, since village-source-wave specific mean indirect utility terms are free parameters. The fit is very close, but not exact, for two reasons. First, the raw data contain zero market shares for some sources that were available in a given village and wave. For example, we take own solar to be universally available and yet there are some villages where no household said they use own solar. These zeros are not surprising in a sample of 30-odd households, but in the model, all sources must have positive shares, though they can be arbitrarily small. To force the data to have positive shares, we implement a Laplace correction (see footnote 26), which raises market shares slightly for sources with low take-up (Table B3, panels A through C, row 2 versus row 1). Second, we classify availability for some sources based on our supply-side data on village-source-level availability, rather than the survey data on household reports. This classification allows us to observe when a source is not offered (as opposed to not bought), and therefore remove the choice from the choice set instead of modeling it as available but not selected. However, in a small number of cases households report buying sources that we do not believe were offered in their village and survey wave, which we attribute to survey misreports. Again, these differences in classification have a very small affect on market shares (Table B3, panels A through C, row 3 versus row 2).

Table B3: Structural Model Fit versus Data

	Market shares				
	Grid (1)	Diesel (2)	Own solar (3)	Micro-grid (4)	All (5)
Panel A. Baseline					
Raw data	5	17	5	1	27
Data with Laplace correction	6	17	7	1	31
Model	6	17	7	0	30
Panel B. Endline					
Raw data	25	3	4	9	40
Data with Laplace correction	24	3	7	10	43
Model	24	3	7	9	43
Panel C. Follow-up					
Raw data	43	3	15	3	64
Data with Laplace correction	40	3	17	5	65
Model	41	3	17	4	65

The table presents market shares in the electricity market, and juxtaposes data vs our model's fit. Data with Laplace correction adjusts each product's market share to ensure that no product has a zero share. Small differences between data with Laplace correction and model for a given wave can exist due to the use of market-level source availability in the model. Data with Laplace correction uses actual household-level availability, and there can be inconsistencies between household-level and market-level availability in the data due to a very small number of households in the control villages saying that they used microgrid solar.

b First stage estimates for structural demand model

Table B4 presents the first-stage from the linear, instrumental variables estimates of the second part of the structural demand model. The endogenous variables are either price, peak hours of supply, or off-peak hours of supply. In columns 1 through 4 the instruments for price are the interactions between the experimental treatment assignments and the endline survey waves. Column 1 gives the first stage for price when instrumenting only for price. Column 2 gives the first stage for price when instrumenting for price, peak hours of supply, and off-peak hours of supply. Columns 3 and 4 give the respective first stage estimates for peak and off-peak hours of supply. Columns 5 and 6 give the first stage estimates of the price equation, when instrumenting for price and both hours measures, and replacing the experimental instruments with instrumental variables constructed along the lines of Berry, Levinsohn and Pakes (1995) and Hausman (1996). We have two sets of alternative instruments for source-village-wave prices. First, the average hours of supply and load from the other products in the same village, which should affect source mark-ups and prices under oligopolistic competition (Berry, Levinsohn and Pakes, 1995). Second, the average price for a given source in the nearest three villages where that source is available, which will covary with source price due to common supply shocks (Hausman, 1996; Nevo, 2001).

Table B4: First-Stage of Linear Estimation of Demand for Electricity

	Price IV	Price & hours IV			Price & hours IV BLP	Price & hours IV Hausman
	Price	Price	Peak hours	Off-peak hours	Price	Price
	(1)	(2a)	(2b)	(2c)	(3)	(4)
Treatment normal price X Endline	0.064**	0.064**	0.0050	-0.0046		
	(0.029)	(0.028)	(0.0051)	(0.030)		
Treatment subsidy price X Endline	-0.16***	-0.16***	0.0075	0.014		
	(0.021)	(0.021)	(0.0063)	(0.031)		
Hours of peak supply	-0.050					
	(0.049)					
Hours of off-peak supply	0.0081					
	(0.013)					
Peak hours instrument		-0.032	0.94***	0.19	-0.040	-0.038
		(0.045)	(0.063)	(0.15)	(0.043)	(0.044)
Off-peak hours instrument		0.0040	0.032**	0.88***	0.0057	0.0051
		(0.0094)	(0.013)	(0.030)	(0.0090)	(0.0091)
Total supply of competing products					-0.0017	
					(0.0060)	
Load of competing products					0.0079	
					(0.011)	
Avg price in nearby villages						0.038
						(0.080)
ξ_{tj} mean effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	999	999	999	999	945	989
First-stage F-Stat	42.1	21.1	524.1	1057.2	0.4	0.5
Control mean	0.95	0.95	4.09	3.07	0.95	0.95

This table presents the first-stage of the IV estimates provided in column 2 through 5 of Table 7. Each outcome variable is an endogenous variable that we instrument for in the IV estimations. The second cluster of columns correspond to our preferred IV specification, which uses our experiment to instrument for price, peak, and off-peak hours of supply. Details on instrument construction for hours of supply can be found in Appendix A, Subsection c. Standard errors are clustered at the village-level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

c Elasticities of substitution

Table B5 presents aggregate own- and cross-price elasticities by source, using the structural demand model. The elasticities are calculated using the full model of demand, using the specification for mean indirect utility in Table 7, column 3 and the specification for household heterogeneity in Table 8, columns 6 through 10. Each entry in the table gives the elasticity of the market share for the column source with respect to the price of the row source.

Table B5: Price Elasticities of Electricity Source Demand

	Elasticity of share for source:				
with respect to price of source:	Grid (1)	Diesel (2)	Own solar (3)	Micro-grid (4)	None (5)
Grid	-0.62	0.33	0.58	0.15	0.15
Diesel	0.06	-1.84	0.24	0.03	0.04
Own solar	0.18	0.39	-1.71	0.10	0.09
Microgrid	0.13	0.14	0.28	-1.53	0.15

The table presents aggregate own- and cross-price elasticities of demand by electricity source. The arc elasticities are calculated using a 10% increase in each source's price from its mean endline price. The elasticities are calculated for the market share of each column source with respect to the price of each row source.

d Marginal effects for alternative household profiles

Table 8 presents the marginal effects of household characteristics on electricity choice probabilities for a "poor" household. Section 4 shows the results of counterfactuals where we increase the income and wealth of households from "poor" to "median" and "rich" levels. This subsection defines these household profiles and shows marginal effects for alternative household profiles to complement the estimates in the main text.

Table B6 shows the characteristics of households that are used to create the three profiles of household covariates. The number of adults (column 1) is integer valued, house characteristics (2 and 3) are indicator variables, the number of rooms is integer valued (4), agricultural land ownership is an indicator variable (5), literacy is integer valued (6) and income is continuous. Each row gives the values that these variables take on for each of the three household profiles we use to calculate marginal effects and to run counterfactuals.

The levels of these variables were chosen in order to roughly place a household, on an univariate basis, at the 20th, 50th and 80th percentile of the income or wealth distributions. Table B8 shows detailed summary statistics for the household covariates that enter our demand model in order to place the household profiles in context.

To calculate the marginal effects of these covariates on choice probabilities, we change their values by either one unit, for dummy variables, or one standard deviation, for integer valued and continuous variables. Table B7 shows the changes that this entails for each household covariate that enters the profiles. For the binary variables (Pukka, roof, land), this approach necessarily means that we cannot calculate the discrete effect for these variables when they are already equal to one in a given profile. For example, we cannot calculate the impact of having a roof for a median household, as a median household already has a roof. We therefore omit these entries from the corresponding tables of marginal effects.

Table B6: Profile Details

	Adults	Pukka	Roof	Rooms	Land	Education	Income (INR)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Poor	2	0	0	1	0	1	3750
Median	3	0	1	2	1	1	6000
Rich	5	1	1	3	1	5	9500

This table details the characteristics for a poor, median, and rich household. Each profile was constructed by independently taking a fixed percentile of each column attribute. The fixed percentiles corresponding to poor, median, and rich are 20, 50, and 80, respectively. For example, a poor household lives in a 1-room dwelling, which corresponds to the 20th percentile of households in our sample across all survey waves.

Table B7: Definition of Household Characteristics and Magnitude of Marginal Change

Characteristic	Definition	Marginal Change (Poor)
Adults	Adults in the household	1 SD (1.83 persons)
Pukka	Indicator for solid house	0 to 1
Roof	Indicator for solid roof	0 to 1
Rooms	Number of rooms in the house	1 SD (1.32 rooms)
Land	Indicator for agricultural land	0 to 1
Education	Education of household head (1-8)	1 SD (2 levels)
Income	Monthly household income	1 SD (INR 6486)

The table defines the household characteristics used in our choice model and shows the magnitude of the change in each covariate for a poor household, as used in the marginal impact analysis of household covariates on choice probabilities (Table 8). Base profiles for a representative poor, median, and rich household can be found in Table B6. Education 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 B8: Summary Statistics of Household Characteristics

	Mean	Median	Q1	Q3	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Adults in the household	3.67	3	2	5	1.83	1	15
Indicator for solid house	0.32	0	0	1	0.47	0	1
Indicator for solid roof	0.51	1	0	1	0.50	0	1
Number of rooms in the house	2.45	2	2	3	1.32	1	11
Indicator for agricultural land	0.63	1	0	1	0.48	0	1
Education of household head (1-8)	2.48	1	1	4	2.04	1	8
Monthly household income (INR)	7576	6000	4000	8500	6486	0	65000
Observations	8822	8822	8822	8822	8822	8822	8822

The table summarizes each of the household covariates used in our structural demand estimation. Each observation is for a household in a specific survey wave.

Tables B9 and B10 show the estimated discrete effects for a median and rich household, respectively, to be compared to Table 8 in the main text. The main finding is that, at all levels of household income, the discrete effects of increasing income or wealth proxies is to increase the demand for grid electricity and decrease, or barely alter, the demand for other sources of electricity. The discrete effects of household characteristics on choice probabilities are slightly smaller for rich than for poor households on some measures (e.g., the effect of income on grid choice), though these differences are small and not generally statistically significant. This relative lack of attenuation may reflect that even rich households, in our sample, have far from complete take-up of any electricity source.

Table B9: Impact of Household Characteristics on Choice Probabilities (Median Household)

	Grid (1)	Diesel (2)	Own Solar (3)	Microgrid (4)	None (5)
Number of adults	0.047	-0.001	0.001	0.003	-0.049
	(0.010)	(0.003)	(0.002)	(0.004)	(0.008)
Solid roof (=1)	-	-	-	-	-
Solid house (=1)	0.097	-0.006	-0.006	-0.009	-0.076
	(0.023)	(0.008)	(0.006)	(0.009)	(0.019)
Number of rooms	0.035	0.005	0.004	0.001	-0.046
	(0.012)	(0.004)	(0.005)	(0.004)	(0.008)
Owns ag. land (=1)	-	-	-	-	-
Education of household head (1-8)	0.036	0.004	-0.002	0.000	-0.039
	(0.009)	(0.004)	(0.003)	(0.004)	(0.007)
Household income	0.019	0.000	0.001	0.014	-0.034
	(0.009)	(0.003)	(0.002)	(0.005)	(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 B12, column 2. Each cell entry is the change in choice probability for a median household from increasing the row characteristics. For discrete household characteristics, the increase is from zero to one. For continuous household characteristics, the increase is for one standard deviation. Appendix Table B6 describes the statistical profile of a poor, median, and rich household. Standard errors are constructed using the delta method.

e Robustness of demand estimates

Table B11 shows estimates of the intent-to-treat effects of the experimental treatment assignments on microgrid demand using administrative data on microgrid payments. These estimates are analo-

Table B10: Impact of Household Characteristics on Choice Probabilities (Rich Household)

	Grid (1)	Diesel (2)	Own Solar (3)	Microgrid (4)	None (5)
Number of adults	0.036	-0.003	-0.000	0.000	-0.033
	(0.008)	(0.003)	(0.001)	(0.004)	(0.005)
Solid roof (=1)	-	-	-	-	
Solid house (=1)	-	-	-	-	-
Number of rooms	0.026	0.003	0.002	-0.001	-0.030
	(0.011)	(0.004)	(0.003)	(0.004)	(0.007)
Owns ag. land (=1)	-	-	-	-	-
Education of household head (1-8)	0.028	0.002	-0.002	-0.001	-0.026
	(0.007)	(0.003)	(0.003)	(0.003)	(0.005)
Household income	0.011	-0.001	0.000	0.011	-0.022
	(0.008)	(0.003)	(0.001)	(0.005)	(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 B12, column 2. Each cell entry is the change in choice probability for a rich household from increasing the row characteristics. For discrete household characteristics, the increase is from zero to one. For continuous household characteristics, the increase is for one standard deviation. Appendix Table B6 describes the statistical profile of a poor, median, and rich household. Standard errors are constructed using the delta method.

gous to the Table 5 estimates in the main text but use administrative data on payments rather than survey data on source usage as the measure of demand. The estimated market share in subsidized price villages is very similar across both data sources, while the estimated market share in normal price villages is higher in the survey data than in the payments data. Payments for microgrids may differ from survey reports due to measurement error or because households still use microgrids, for a time, even after they have stopped paying the monthly price. We understood from our field work that the pace at which HPS repossessed systems for non-payment was slow.

We specify a nested logit demand model, which requires an ex ante choice of nest structure. Since different sources of electricity differ on multiple dimensions, it is not obvious for what sources demand should be expected to unobservably correlate. Table B12 presents coefficients from the non-linear part of the demand model for alternative nest structures. Column 1 gives coefficients from a multinomial logit model, in which there is no correlation between the unobserved taste shocks for different sources. Columns 2 and onwards then give coefficients from nested logit models with varying nest structures. The last two coefficients in the table are the parameters that govern the

Table B11: Solar Microgrid Demand by Village Treatment Arm

	Administrative		
	Baseline (1)	Endline (2)	Paid ever (3)
Treatment: Subsidized price	0.033	0.179***	0.271***
	(0.025)	(0.052)	(0.066)
Treatment: Normal price	0.003	0.013	0.022
	(0.002)	(0.010)	(0.034)
Constant	0.000	0.005	0.030
	(0.000)	(0.005)	(0.029)
Observations	100	100	100

The table shows estimates of microgrid demand by treatment status. The dependent variable is the village-level market share of microgrid solar from HPS administrative payments data, which measures whether households have paid for the source recently. There are three treatment arms: a subsidized price arm (microgrids offered at INR 100), a normal price arm (microgrids offered at the prevailing price of INR 200, later cut to INR 160 in some villages), and a control arm (microgrids not offered). Each column measures market share for a specific time frame: the household paid in the first month after baseline; the household paid in the three months leading up to the endline; the household ever paid. Standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

correlation of the logit shocks within nests.

There are two main points from the table. First, we have chosen the column 2 specification as our main specification, since it achieves the highest log likelihood. Our main estimates therefore come from using a nest structure that assigns microgrids and the outside option to their own nests, and grid, diesel and own solar to a third nest. Second, while these estimates achieve the highest log likelihood, the assumed nest structure has very small effects on both the log likelihood of the model and the coefficients on household characteristics. All of the models, including the multinomial logit model, yield very similar coefficients on household observables.

Since the nest structure may affect the coefficients on observable characteristics, in the non-linear part of the structural model estimation, it may then change the dependent variable and estimates in the second, linear part of the structural model also. Table B13 shows estimates of the second, linear part of the structural demand model, where alternative nest structures have been used in the first stage. The coefficient on price is very close to our main estimate across all specifications. The coefficient on hours of peak supply is somewhat more variable, but imprecise, and not significantly different from our main estimate in any alternative specification.

Table B12: First-Stage Estimation Results for Alternative Nest Specifications

γ_{jr}	Multinomial Logit (1)	{Grid, Diesel, Own solar} & {Microgrid} (2)	{Grid, Diesel, Microgrid} & {Own solar} (3)	{Grid, Own solar, Microgrid} & {Diesel} (4)	{Grid} & {Non-Grid} (5)	{Grid, Own solar} & {Diesel, Microgrid} (6)	{Grid, Diesel} & {Solars} (7)
Grid × Income	0.21	0.19	0.21	0.21	0.20	0.21	0.21
	(0.06)	(0.05)	(0.06)	(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)	(0.05)	(0.14)	(0.08)
Own solar × Income	0.16	0.18	0.16	0.17	0.20	0.16	0.17
	(0.07)	(0.06)	(0.07)	(0.07)	(0.05)	(0.13)	(0.20)
Microgrid × Income	0.50	0.49	0.50	0.48	0.25	0.50	0.49
	(0.11)	(0.11)	(0.14)	(0.13)	(0.00)	(0.13)	(0.49)
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)	(0.09)
Diesel × Land	-0.15	-0.09	-0.15	-0.15	-0.01	-0.15	-0.15
	(0.12)	(0.11)	(0.12)	(0.12)	(0.00)	(0.15)	(0.12)
Own solar × Land	0.15	0.18	0.15	0.16	0.11	0.15	0.16
	(0.11)	(0.09)	(0.11)	(0.12)	(0.00)	(0.17)	(0.22)
Microgrid × Land	0.21	0.20	0.21	0.20	0.08	0.21	0.19
	(0.17)	(0.17)	(0.17)	(0.16)	(0.06)	(0.17)	(0.42)
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)	(0.02)
Diesel × Adults	0.09	0.09	0.09	0.09	0.08	0.09	0.09
	(0.04)	(0.03)	(0.04)	(0.04)	(0.01)	(0.06)	(0.03)
Own solar × Adults	0.09	0.10	0.09	0.09	0.10	0.09	0.09
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.06)	(0.03)
Microgrid × Adults	0.09	0.09	0.09	0.09	0.10	0.09	0.09
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)
Grid × Pukka	0.42	0.36	0.42	0.41	0.42	0.42	0.42
	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Diesel × Pukka	0.13	0.20	0.13	0.13	0.09	0.13	0.15
	(0.14)	(0.11)	(0.14)	(0.14)	(0.10)	(0.16)	(0.15)
Own solar × Pukka	0.11	0.16	0.11	0.11	0.09	0.11	0.11
	(0.12)	(0.10)	(0.12)	(0.12)	(0.09)	(0.15)	(0.32)
Microgrid × Pukka	-0.01	-0.00	-0.00	0.02	0.12	-0.00	0.02
	(0.19)	(0.19)	(0.21)	(0.20)	(0.10)	(0.19)	(0.86)
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)	(0.02)
Diesel × Lit	0.09	0.08	0.09	0.09	0.06	0.09	0.09
	(0.03)	(0.02)	(0.03)	(0.03)	(0.00)	(0.06)	(0.03)
Own solar × Lit	0.02	0.05	0.02	0.02	0.04	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)	(0.03)	(0.02)
Microgrid × Lit	0.05	0.05	0.05	0.05	0.06	0.05	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)
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)	(0.10)
Diesel × Roof	0.20	0.28	0.20	0.20	0.23	0.20	0.20
	(0.13)	(0.11)	(0.13)	(0.13)	(0.05)	(0.17)	(0.14)
Own solar × Roof	0.42	0.44	0.42	0.41	0.32	0.42	0.40
	(0.12)	(0.09)	(0.12)	(0.11)	(0.00)	(0.29)	(0.38)
Microgrid × Roof	0.00	0.00	0.00	0.03	0.22	0.00	0.02
	(0.18)	(0.18)	(0.19)	(0.20)	(0.00)	(0.18)	(0.84)
Grid × Rooms	0.13	0.14	0.13	0.14	0.13	0.13	0.13
	(0.03)	(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)	(0.03)	(0.10)	(0.05)
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)	(0.03)	(0.11)	(0.06)
Microgrid × Rooms	0.10	0.10	0.10	0.10	0.15	0.10	0.11
	(0.07)	(0.07)	(0.07)	(0.06)	(0.03)	(0.07)	(0.15)
σ_1	-	0.55	0.01	0.10	0.82	0.01	0.10
		(0.20)	(0.28)	(0.32)	(0.00)	(0.43)	(0.42)
σ_2	-	-	-	-	-	0.01	0.08
						(0.39)	(5.06)
Observations	8822	8822	8822	8822	8822	8822	8822
Log likelihood	-5793.31	-5791.36	-5793.35	-5793.27	-5791.67	-5793.37	-5793.12
LR test statistic	-	3.91	-0.07	0.08	3.29	-0.10	0.38
LR test p value	-	0.05	1.00	0.78	0.07	1.00	0.83

Our likelihood ratio test statistic is $LR = -2\{LL(\theta_{constrained}) - LL(\theta_{unconstrained})\}$ Each of the nested logit specifications (columns 2 through 7) is 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 the log of the likelihood function).

Table B13: Linear Estimation of Demand for Electricity (Alternative Nests)

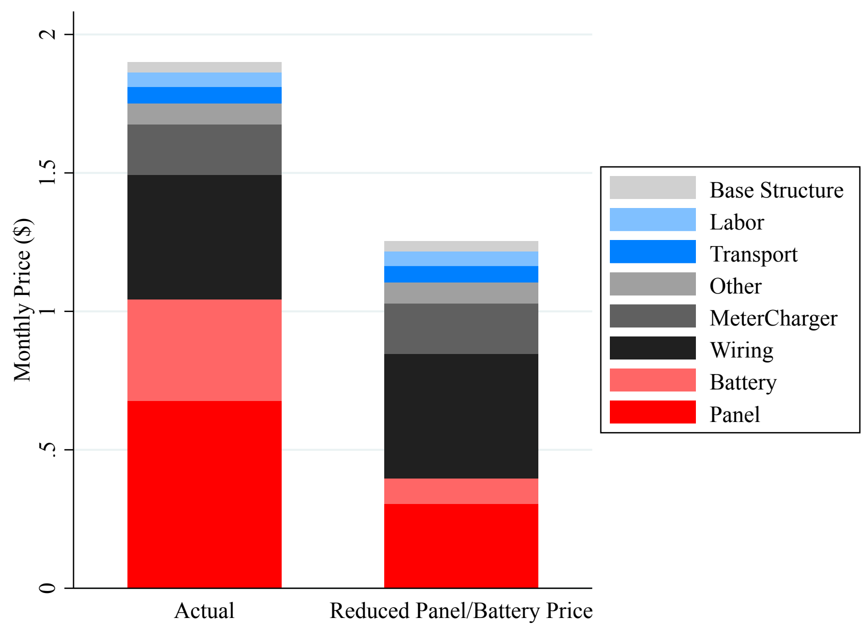
	Nested Logit			
	{Microgrid} {Non-Microgrid}	{Solar} {Non-Solar}	{Grid} {Non-Grid}	Multinomial Logit
	(1)	(2)	(3)	(4)
Price (Rs. 100)	-1.70***	-1.60**	-1.74**	-1.58**
	(0.63)	(0.64)	(0.72)	(0.64)
Hours of peak supply	0.21	0.44	0.47	0.47
	(0.27)	(0.30)	(0.30)	(0.30)
Hours of off-peak supply	-0.11*	-0.16**	-0.17**	-0.17**
	(0.058)	(0.065)	(0.066)	(0.065)
ξ_{tj} mean effects	Yes	Yes	Yes	Yes
Observations	999	999	999	999
First-stage F-Stat	21.1	21.1	21.1	21.1

The table presents linear estimation of our demand system, using alternative nest structures in the non-linear estimation. The dependent variable are the mean indirect utilities, specific to each village and survey wave, which come from the non-linear first-stage estimation. The first column uses our preferred nest structure of grouping grid, diesel, and own solar in one nest and microgrid in its own nest. (The estimates in the first column are the same as those in column 3 of Table 7.) The second column uses a nest structure 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 non-grid technologies in a second nest. In the last column, we use the mean indirect utilities derived from a multinomial logit first-stage estimation. For all second-stage linear estimations, we instrument for price, peak hours, and off-peak hours. Peak hours refers to electricity supply during the evening (5 - 10pm). All regressions control for wave × source mean effects. Standard errors are clustered at the village-level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Appendix: Counterfactual Scenarios

This section gives additional details on our counterfactual scenarios. Figure C4 shows the breakdown of costs for solar microgrids, which we use to forecast the effects of declines in the prices of solar photovoltaic panels and batteries on solar systems. Because the capital cost of PV panels and batteries make up a significant, but incomplete, share of total cost, this breakdown is necessary to calculate the effect that any proportional decline in capital costs will have on the total costs of solar systems.

Figure C4: Microgrid Solar Cost Structure: Current and Predicted



In this figure, we show the cost components of a microgrid, to provide transparency on how we derived the solar prices in our counterfactual scenarios involving a fall in solar prices. We only take into account price changes for solar photovoltaics and batteries, which are clearly correlated with R&D. We assume a 55% reduction in the cost of solar PV, which is in line with the National Renewable Energy Laboratory's projections for 2022. For batteries, we assume a cost reduction of 75%, in accordance with the US Department of Energy's 2022 goal. These two changes translate into a 30% reduction in the overall price of a microgrid. We use the same proportional change in price for own solar in our counterfactuals.

For reference, Table C14 enumerates the assumptions in our counterfactual scenarios from Table 9. Column 1 gives the name of each scenario and columns 2 through 4 detail assumptions made in the row scenario regarding source availability, supply hours, pricing and subsidies, and any additional details.

Table C14: Counterfactual Analysis: Assumptions

Scenario	Source availability	Source hours (peak)	Other notes
Improved solar	Follow-up	Follow-up	Solar technologies at their market characteristics as of the follow-up survey, with consumer characteristics held constant at baseline levels
Improved grid	Follow-up	Follow-up	Grid technology at its market characteristics as of the follow-up survey, with consumer characteristics held constant at baseline levels
Solar cost falls	Follow-up	Follow-up	Reduction in microgrid price from INR 170 to INR 120 (based on 2022 projection), proportional (30%) reduction in own solar price
Grid in all villages	Follow-up for diesel and solar, grid everywhere	Follow-up	
Increase peak grid hours	Follow-up	Two additional peak hours for grid (capped at 5 hours), follow-up peak hours for all other sources	
All households at least X	Follow-up	Follow-up	Each household covariate is at least as large as it is under profile X where $X \subset \{\text{Median}, \text{Rich}\}$. Profile *Rich* corresponds to the 80th percentile (details on each profile can be found in Appendix Table B6)
Reduce theft	Follow-up	Follow-up	Increase grid price from INR 60 to INR 115 to keep producer losses at follow-up level