

Pre-Analysis Plan

Shedding light on constraints to moving up the renewable energy ladder: Experimental evidence from solar investments in rural Senegal

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Date of latest draft: 08/05/2024

Abstract

Despite the expansion of the electricity grid, the adoption and use of grid electricity remains low in low- and lower-middle-income countries. Increased access to decentralized solar power is seen as an attractive solution to enhance electricity consumption, as the recurrent cost of consumption is effectively zero and households can dynamically optimize their desired service levels. A randomized experiment among 1,200 households in 150 villages in rural Senegal will test whether the free provision of entry-level solar energy investments has long-term effects on electricity demand. The outcomes of interest are revealed measures of the willingness to pay for a solar lamp of the same scale provided eight years ago and for a larger solar home system. Additionally, we consider the electricity tier, that the households have access to, as an outcome of interest. We use additional features of the study design to explore spillover effects and unpack potential mechanisms such as development and knowledge effects.

Keywords: renewable energy, technology adoption, vertical upscaling, solar kits, one-off subsidy, learning-by-doing, willingness to pay

JEL codes: D12, D83, O1, O13, Q41, Q42

Study pre-registration: The baseline was registered on 09 December 2015 as AEARCTR-0000977; <https://www.socialscisearch.org/trials/977>. This PAP will be added to the same AEA RCT Registry code after endline data collection, but before the analysis.

Timeline

December 2023:	survey pilot
mid-January – mid-March 2024:	endline data collection
May – July 2024:	data cleaning and analysis

1. Introduction

Research question: background, importance and relevance

Increasing electricity access and use is strongly associated with economic growth in high- and middle-income countries (e.g., Kline and Moretti 2014; Lipscomb, Mobarak, and Barham 2013; Kassem 2021; Dinkelman 2011). In contrast, recent experimental and quasi-experimental studies in low- and lower-middle income settings have found surprisingly limited economic impacts of providing grid electricity (Lee, Miguel, and Wolfram 2020a; 2020b; Lenz et al. 2017; Burlig and Preonas, forthcoming). Moreover, once connected, households' electricity use in this context remains below levels that would allow utilities to be economically viable (e.g., Lee, Miguel, and Wolfram 2020a; 2020b; Hsu and Van Vuren 2023). These findings raise important concerns for future electrification strategies given the remaining global population without access to any type of electricity lives in low- and lower-middle-income countries (World Bank 2023).

Countries often combine their electricity infrastructure investments with tariff subsidies aimed at lowering the marginal cost of grid electricity for low-income households, which is an important driver of use (Jack and Smith 2020; Ledger and Rampedi 2022; Allcott, Collard-Wexler, and O'Connell 2016; Burgess et al. 2019). However, lowering grid electricity tariffs is problematic for various reasons: most electric utilities in Sub-Saharan Africa already operate at a loss with tariffs lower than production costs (Trimble et al. 2016) and government subsidies will be constrained by low economic growth expected over the next decade (Kose and Ohnsorge 2023). Even if resources were available, subsidizing electricity consumption (beyond connection costs) creates market distortions (Burgess et al. 2020) and can produce a low-quality infrastructure equilibrium with limited economic structural change (McRae 2015; Hsu and Van Vuren 2023; Burgess et al. 2020).

Decentralized solar power solutions offer two unique features that make them potentially attractive in poor economies (Deichmann et al. 2011). First, the recurrent consumption cost is effectively zero, addressing potential usage constraints. Second, a wide range of relatively low entry-cost service levels is available from basic solar lamps to systems able to power entire households and small businesses. This allows households to dynamically optimize service levels. An important unexplored question in the literature is whether entry-level investments into electricity supply at zero marginal costs induces households to incrementally scale up solar power as their demand increases as they learn about the benefits of electricity and their ability to pay rises due to income effects with important implications for economic development (Wolfram, Shelef, and Gertler 2012). Do households remain locked in a low-electricity-use equilibrium because the upfront investment costs for higher-scale systems remain an important barrier to adoption (e.g., Berkouwer and Dean 2022) and high tariffs limit intensive use? And could modular solar electrification allow households to incrementally increase the use of low-cost electricity in the longer run? Understanding this long-run electricity investment and use path for households would

have significant implications for whether off-grid renewable energy should be included as an important pillar in electrification strategies for the remaining unelectrified households in the world.

This study examines whether households in rural Western Senegal can scale up renewable energy investments after being provided with entry-level electricity service. We conducted a randomized controlled trial in 2016 across 150 villages where 1,200 households were randomly assigned to receiving a high-quality solar lamp, or to a control group. These lamps provide basic lighting and phone charging capabilities, meeting the first level of energy access (Tier 1) defined by the World Bank's multi-tier framework (Bhatia and Angelou 2015).¹ We use this experimental variation to test how electricity consumption evolves in the long run when households initially access low levels of electricity service at zero marginal cost. Specifically, we return to these households eight years later to measure willingness to pay (WTP) for a new Tier 1 solar lamp and a larger solar home system that meets the requirements for the next level of the electricity access ladder in the multi-tier framework (Tier 2). We will also observe whether households have made any other investments in electricity access during this period (such as purchasing additional solar products or connecting to the grid, where this has become available). We then test for spillovers by measuring whether households in close geographic proximity to those having received the solar lamps are more likely to invest in solar products and/or grid electricity during the eight-year period prior to the endline, and whether they have an increased WTP for Tier 1 or Tier 2 services. Finally, we use additional features of the study design to explore income and learning effects, which are two potential mechanism that induce households to upscale their energy demand.

This document outlines the plan for analyzing the previously described agenda by combining baseline data from eight years ago with recently collected endline data. In the next section, we lay down the research design including the intervention and all research questions with associated hypotheses. We describe the different data in Section 3. Section 4 explains the empirical strategy and Section 5 maps out our contribution to the existing literature. Note that this document was written up after the collection of endline data, but before the analysis. This pre-analysis plan lays down various research hypotheses, which we initially foresee to treat in one research article. However, depending on the extend of the findings, we may examine the different hypotheses either in separate research articles.

¹ The multi-tier framework goes from Tier 1 (basic lighting and cell phone charging for 4 hours a day) to Tier 5 (reliable service of at least 8.2 KWh consumption a day). Tier 0 (less than 12 Wh a day) does not count as having access to electricity. More information can be found at: <https://mtfenergyaccess.esmap.org/methodology/electricity>

2. Research Design

Intervention

In 2016, the World Bank Lighting Africa initiative, in coordination with DIME, distributed high-quality solar lamps² in 150 villages across two regions of Western Senegal: Thiès and Diourbel.

The d.light s300 solar lamp was distributed free of charge to a random subset of 300 households across the 150 villages (i.e., two households per village). The device (see Figure A.1 in the appendix) is fully solar rechargeable, produces 100 lumens of light (which is enough to light up a small room), and allows for cell phone charging. It is certified by the World Bank’s Lighting Africa initiative and has an expected five-year lifetime.

Baseline data were collected between March and June 2016 from a total of 7,085 households across the 150 villages (i.e., on average 48 households per village). Eight households per village received a longer and more detailed survey in person (“long-survey households”). Two of these households per village were randomly assigned to **treatment** (receiving the d.light 300 free of charge) while the remaining six households per village were assigned to **control**. This resulted in a total of 300 treatment and 900 control households. The remaining 40 households per village received a short survey in person (“short-survey households”) and will serve for the analysis of spillover effects.

Households were not blinded to their intervention. However, the likelihood of Hawthorne, John Henry, or experimenter demand effects were minimized by not explicitly telling subjects that the solar lamps are part of an experiment. The baseline survey was introduced as a research study about energy usage in rural Senegal to inform the World Bank’s project work. Before starting the survey, households provided their informed consent. One of our main outcomes of interest will be revealed WTP that, because of real monetary stakes, is less likely to be affected by any experimenter demand effects relative to stated outcome measures. For the participation in the WTP exercise, households were required to give additional informed consent.

Hypotheses

Primary Hypotheses

Hypothesis 1a:

(Long-term) exposure to a free solar lamp increases investments in (on- or off-grid) electricity (including WTP for future solar products).

Our treatment represents a Tier 1 product on the ESMAP/SE4All Multi-Tier Framework (MTF) for Measuring Energy Access (Bhatia and Angelou 2015). The solar lamp is easily scalable, is

² Solar lamps come with a solar panel that charges the battery by producing electrical energy from sunlight.

provided for free, and produces electricity to power a light as well as charge cell phones at zero marginal cost. We hypothesize that households have imperfect information about the utility of the product (i.e., the lamp's features, and usefulness for the household and productive activities) and that the provision of a free (high-quality) solar lamp increases the chance of intensive use. Households will be given (i) the opportunity to experience the product and learn about its qualities (see e.g., Dupas 2014; Bensch and Peters 2020; Meriggi, Bulte, and Mobarak 2021), and (ii) potentially save on other energy expenditures (e.g., Grimm et al. 2017; Aevarsdottir, Barton, and Bold 2017; Mahajan, Harish, and Urpelainen 2020; Wagner et al. 2021) and potentially experience more income gains through productivity effects (e.g., Mahajan, Harish, and Urpelainen 2020; Aevarsdottir, Barton, and Bold 2017). Such *learning* and *income* effects positively affect the subsequent demand for solar lighting technologies of the same or higher levels of service, pushing households up the energy ladder over time. Where grid electricity became available, households may even invest in connecting to the grid. Observing this transition process over a long timeframe of eight years (exceeding the lifetime of the distributed solar lamp) helps to measure the accumulated learning and income effects. To minimize the potential of households being negatively affected by a poor-quality solar product, we ensure all households are provided with a Lighting Global-certified product with a lifetime expectancy of five years.

Outcomes:

We will test this primary hypothesis 1a through measuring the **revealed WTP** for two different solar lighting products: (i) the Sunshine 300; a solar lamp of similar quality, scale and tier as the d.light s300³; and (ii) a solar home system SPARK; a larger-scale and higher-tier solar lighting product. The solar home system is a modular system that comes with two batteries, one solar panel and four lights, but enables households to also run more powerful appliances such as a TV⁴, fan, or other small-scale productive assets like hair clippers, qualifying therefore as a Tier 2 product on the SE4All MTF.⁵

For each solar lighting product, we will elicit revealed WTP with the Becker-DeGroot-Marschak (BDM) method (Becker, DeGroot, and Marschak 1964). Respondents will be asked the highest price they would be willing to pay, with the understanding that, if a randomly drawn amount is below this price point, they can buy the item for the randomly drawn price. If the randomly drawn amount is higher than this price point, they will not have the opportunity to buy the product. The BDM process is an incentive-compatible approach for eliciting revealed WTP (Berry, Fischer, and Guiteras 2020; Burchardi et al. 2021) and overcomes many of the biases associated with other

³ The initial purpose was to offer them the same lamp that they received at baseline: the d.light s300. However, the company producing this lamp told us that they discontinued the line. The Sunshine 300 by TotalEnergies is similar in terms of scale as well as quality.

⁴ By adding two additional batteries.

⁵ The research team cooperated with the solar firm Vitalité, who delivers the solar home system to households who purchase one in the course of the BDM and manage monthly payments.

forms of elicitation (e.g., Blumenschein et al. 2008).⁶ The procedure has the additional benefit of generating an exact demand per individual compared to a take-it-or-leave-it approach, which generates a truncated distribution.

Solar lamps will be paid for upfront only, meaning that the device will be handed over to the participant only if s/he pays the full amount due. The solar home system, on the other hand, will be offered through a Pay-As-You-Go model. Participants will benefit from a payment plan that allows them to pay in fixed monthly installments over a predetermined period of 14 months⁷, addressing concerns for liquidity constraints. Therefore, instead of eliciting the WTP for the full product as with the solar lamp, we will ask for the monthly WTP for the solar home system (i.e., the fixed monthly amount the respondent would be willing to pay over a 14-months period). The solar home system will be installed and activated only if s/he pays the first monthly payment.

We will randomize the order of the two different solar lighting products when eliciting the WTP. Moreover, due to liquidity constraints, the price draw will only be conducted for one of the two solar lighting products. The solar product to be offered will be determined by a random draw and the fact that the household will only participate in a draw for one of the products will be explained to the respondent before the first WTP elicitation is conducted.

Households will moreover be asked about investments in on- and off-grid energy sources in the past eight years to assess the electricity tier to which the households have access. Following the classification of the Multi-Tier Framework for measuring access to electricity, households will be asked whether they are connected to the electricity grid (if it became available in their village) and whether they own any off-grid electricity sources. Depending on the source of electricity, we will ask about all applicable attributes to assess the respective Tier: capacity, availability, reliability, quality, affordability, formality, and health and safety (World Bank and WHO 2021). This also includes questions on the price paid for the product(s) and/or the monthly expenditures for the grid connection (split by connection and consumption costs). Taken together, this information will serve as an additional outcome to assess whether the treatment led to any other investments into (different tiers of) electricity in the past eight years among treated compared to control households.

Apart from investments in electricity, we elicit the current energy consumption. This includes asking for the ownership of different lighting and electronic devices, and the respective usage levels, which allows us to calculate an estimate of the household's energy consumption. For households connected to the grid, we can directly infer the electricity consumption from the electricity meters. This information will serve to explore the intensive margin of electricity

⁶ If the participants overstate their real reservation prices, they have to buy the product at a price higher than their actual valuations. However, by understating their real reservation prices, they might miss a purchase opportunity at a price less than or equal to their valuations.

⁷ It is important to notice that Pay-As-You-Go schemes are common payment methods in the market for solar home systems (see e.g., Muchunku et al. 2018).

consumption to elucidate whether the treatment not only leads to better electricity access among treated compared to control households, but also translates into higher consumption of electricity. We will analyze the intensive margin either among all households or on a conditional sample of households (under the premise that e.g. the adoption of grid electricity is evenly distributed among the treatment and control group).

Hypothesis 1b:

Free solar lamp experience generates spillovers to neighbors that did not receive the lamp, which increases their investments in (on- or off-grid) electricity (including WTP for future solar products).

Effects experienced by those receiving the free lamp may spill over to others in the community and affect their demand for the distributed Tier 1 and Tier 2 solar power technology. Hence, apart from exploring direct effects among treated households through experience or realizing their potential for productive usage, we also assess effects among households living in close geographic proximity. Ignoring these spillover effects could lead to an underestimation of the impact of the intervention of interest.

We will test this second primary hypothesis 1b on spillover effects through measuring the **revealed WTP** among a selected sample of short-survey households for the two different solar lighting products: a solar lamp and a solar home system. We will follow the same BDM exercise and apply the same questions on electricity investments and consumption as described under the first primary hypothesis with long-survey households. A detailed description of the selection of spillover control and treatment households is given in the sub-section on the sample(s) in Section 3.

Secondary Hypotheses

The secondary hypotheses examine the mechanisms through which the intervention is expected to have an impact on demand for the Tier 1 and Tier 2 solar lighting product.

Hypothesis 2a:

Owning a free solar lamp has positive effects on development outcomes in the long term, including income effects through (i) reduced energy costs and (ii) increased energy use with productivity gains.

A growing number of studies have provided evidence that solar lighting products have a positive effect on development outcomes such as household income in the form of lower expenditures for traditional lighting and energy sources (e.g., Grimm et al. 2017; Aevarsdottir, Barton, and Bold 2017; Mahajan, Harish, and Urpelainen 2020; Rom 2018) or productivity gains (e.g., Aevarsdottir,

Barton, and Bold 2017; Mahajan, Harish, and Urpelainen 2020), children's education (Grimm et al. 2017), and health (Rom 2018).

We will test whether the free provision of a high-quality solar lamp and subsequent intensive use lead to improved **development outcomes**, which in turn affects demand for Tier 1 and Tier 2 solar lighting products or grid electricity (if available), respectively. Specifically, we will examine the impact on the following outcomes:

1. *Monthly income*: Measured by asking the household about how much cash in CFA Franc they earned in the last month from the following income sources: farming activities (including livestock), non-farming activities (e.g., small business), wages, renting of properties, social security benefits (e.g., retirement), and (inter)national remittances. All income sources will be aggregated to one income measure, though we will also differentiate the impact on income from non-farming activities in a separate regression.
2. *Monthly expenditures on energy sources for lighting*: Measured through asking the household about expenditures in CFA Franc on the sources for the last month: biogas, LPG, gasoline, kerosene/paraffin, oil, candles, firewood, dry-cell batteries, generators, solar energy products and grid connection.
3. *Household business*: Measured through asking whether one or various household members operate any non-agricultural or business enterprise within household/compound. As an additional step, we will distinguish between businesses that use electricity and those that do not.
4. *Time spent on domestic work*: Measured through asking time spent on domestic work/housework the day preceding the survey for the household head, spouse and oldest child.
5. *Time spent on income-generating work*: Measured through asking time spent on income-generating work the day preceding the survey for the household head, spouse and oldest child.
6. *Time spent on studying*: Measured through asking time spent on studying both at school and at home, both at daylight and after nightfall for the oldest child enrolled in school.

Development – and particularly **income effects** may take some time to materialize, which is why we consider a long-term time horizon of eight years.

Hypothesis 2b:

Exposure to a free solar lamp generates learning effects about potential productive uses over time; especially if being exposed to behavioral awareness campaigns on solar lighting products.

We will directly assess learning effects through a set of knowledge questions on solar lamps and solar home systems. This includes knowledge about the duration of charging the respective solar lighting products, potential devices than can be run with the respective solar lighting products, and the general understanding of power requirements of different devices.

We hypothesize that **knowledge** of the functionality of solar lamps and solar home systems is a function of past exposure to solar lighting devices, which means that knowledge is higher among treated compared to control households. The higher knowledge, in turn, can lead to a higher valuation of further solar lighting products (Mahadevan, Meeks, and Yamano 2023).

Additionally, we will indirectly assess learning effects through exposure to an informational awareness campaign. A **behavioral awareness campaign** (BAC) was rolled out as a clustered randomized design in the same 150 villages in 2016 relying mainly on community outreach print materials with the aim of enhancing awareness, understanding, and demand for solar lighting products.⁸ The 150 villages were divided into a BAC-control group (100 villages) and a BAC-treatment group (50 villages).⁹ In the BAC-treatment villages, flyers were distributed in frequented areas of the village illustrating the main applications of solar lamps available at local markets and the associated benefit, with the objective of simplifying choices for households (see Figure B.1 in the appendix for an example).

We hypothesize that **information** on the main applications of solar lamps and the associated benefits increases households' knowledge and reinforces use of the distributed solar lamp for productive uses among the treatment group located in the BAC-treatment villages through **learning effects**, leading to stronger effects on subsequent demand for Tier 1 and/or Tier 2 solar lighting products and reinforcing the income effects mentioned in Hypothesis 2a.¹⁰

Basic methodological framework / identification strategy

The main intervention (i.e., the distribution of solar lamps) follows an individual-level randomized experiment, where the level of intervention is the household. The secondary intervention (i.e., the BAC) follows a cluster-level randomized experiment, where the level of intervention is the village. Figure 1 summarizes the intervention (i.e., main and secondary intervention) and survey structure.

We will exploit that the spatial location of treatment households is random to analyze spillover effects among neighboring households (Pollmann 2023). For this, we will compare households

⁸ See Coville et al. (2019) for details of this experiment.

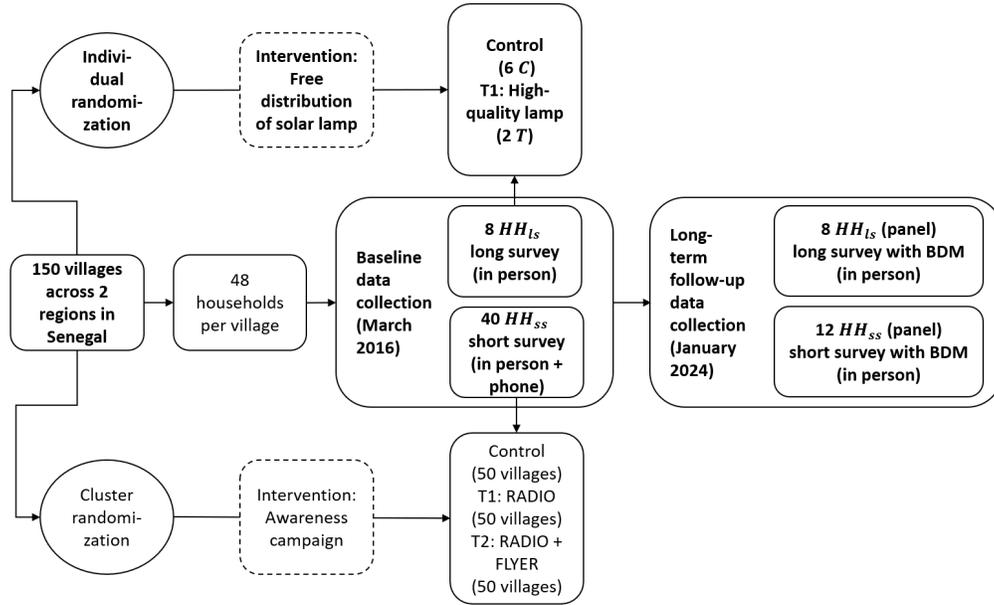
⁹ Additionally to the distribution of print material, the BAC also consisted of a radio campaign providing general information about benefits and quality of solar lamps. The radio campaign was implemented in 50 of the 100 control villages and in all 50 villages where the print material was distributed. To induce exogenous variation in exposure, people were incentivized to listen to the radio in treatment villages, following the approach taken by Berg and Zia (2017). Yet, Coville et al. (2019) do not find any effects of the radio campaign on uptake of solar lamps, which is why in this study, we will focus on the effect of the print material that specifically singled out the most suitable lamp type for all main technological applications.

¹⁰ Mekonnen et al. (2023) assess the WTP for solar lamps in Ethiopia and test whether the provision of information about private and public benefits of the solar lamp has significant effects. Yet, they do not find that information increases adoption rates and WTP.

near locations that are randomly chosen for treatment to households near locations that could have been chosen but were not (i.e., control group household neighbors).

We discuss in the analysis section the planned estimation methods (see Section 4).

Figure 1: Intervention and survey design



Note: The main intervention with the relevant survey observations is highlighted in bold.

3. Data

Sample

Selection of villages and households at baseline

At baseline, the 150 villages in the regions of Thiès and Diourbel were selected based on proximity (i.e., within an 8km radius) to (major) weekly local markets, and proximity to the capital. For the geographical dispersion of the villages across the Thiès and Diourbel regions see Figure C.1 in the appendix.

Before the selection of households, a team of four enumerators spent half a day in each village and visited as many households as possible through a census door-to-door listing, with an average of 40-50 completed household listed per village. The starting point of the listing in each village was the village center (i.e., typically the community center or village leader's office) that was identified by the supervisor, usually in coordination with the village leader.

Households were considered eligible for the baseline study if:

- a) the household head, spouse of the household head, adult child of the household head, or another adult household member was available
- b) the household used a cell phone that was able to receive calls or messages at home
- c) the household provided a valid phone number
- d) the household provided informed consent

The criteria b) and c) facilitate the endline survey (see subsection on variations from intended sample size below).

Baseline data were collected in March 2016 from 7,085 households across the 150 villages (i.e., an average of 48 households per village). Four enumerators completed as many surveys as possible in half a day with a minimum of 40 surveys per village. The village center was identified as the starting point in each village, which was typically the community center or village leader's office, and the exercise systematically worked through proximate residential properties. A household was defined as a group of individuals living together and putting together part or all of their resources to meet their basic needs (housing and food in particular). We distinguish between (i) long-survey households (HH_{ls}) and (ii) short-survey households (HH_{ss}). The second and fourth household per enumerator was selected to receive the longer and more detailed survey in person. Among the eight long-survey households per village, two households were randomly selected to receive a d.light s300 free of charge after the baseline interview ("Treatment Group T ") and the remaining six long-survey households did not receive the solar lamp ("Control Group C "). The remaining randomly selected 40 households per village received

a short survey in person, which was supplemented by additional questions asked over the phone a week later.¹¹

Baseline data indicates that the villages consist of on average 942 people. In 2016, approximately 50% of households in our sample had monthly incomes of 50 USD or less to support household sizes of twelve people on average. Dry-cell battery torches were the most common source of lighting (74% of households used them for some of their lighting needs and 45% of households as the principal lighting source). While solar technologies were available and used (approx. 26% of households had at least one), almost all of these were of lower quality than the d.light s300 solar lamp.

For the endline survey eight years after the baseline, we revisited the eight long-survey households and administered the same long questionnaire from the baseline with additional questions on development outcomes, electricity investments (including current connection to the grid and ownership of off-grid electricity sources), energy usage and social networks such as conduct the BDM exercise for the solar lamp and a solar home system with follow-up questions on intended use of the respective solar lighting products. We only revisited a subsample of the short-survey household and administered the same endline questionnaire with the BDM exercise that we apply to the long-survey households to the sub-sample of short-survey households. The selection of the subsample is described in the next section.

Selection of spillover households

We assume geographic space to be a reasonable proxy for the social network, through which treatment households may share their experience with the high-quality solar lamp. For the analysis of such spillover effects, we will therefore focus on short-survey households HH_{SS} which reside in close proximity to long-survey households HH_{LS} . Specifically, we will select as “neighbors” the two closest HH_{SS} to each treated household T and the two closest HH_{SS} to four out of six¹² control households C .¹³ The selected HH_{SS} households will be defined as treatment spillover (TS) or control spillover (CS) based on their proximity to either T and C , respectively (see Table 1 for the final endline sample composition):

- TS = treatment spillover; i.e., households neighboring a treatment household (assuming that spillover effects occur)
- CS = control spillover; i.e., households neighboring a control household (assuming that no spillover effects occur)

¹¹ The short-survey households were initially selected for the evaluation of the behavioral awareness campaign. For this study, they will moreover serve for the analysis of spillover effects.

¹² We only select four out of six for budget reasons.

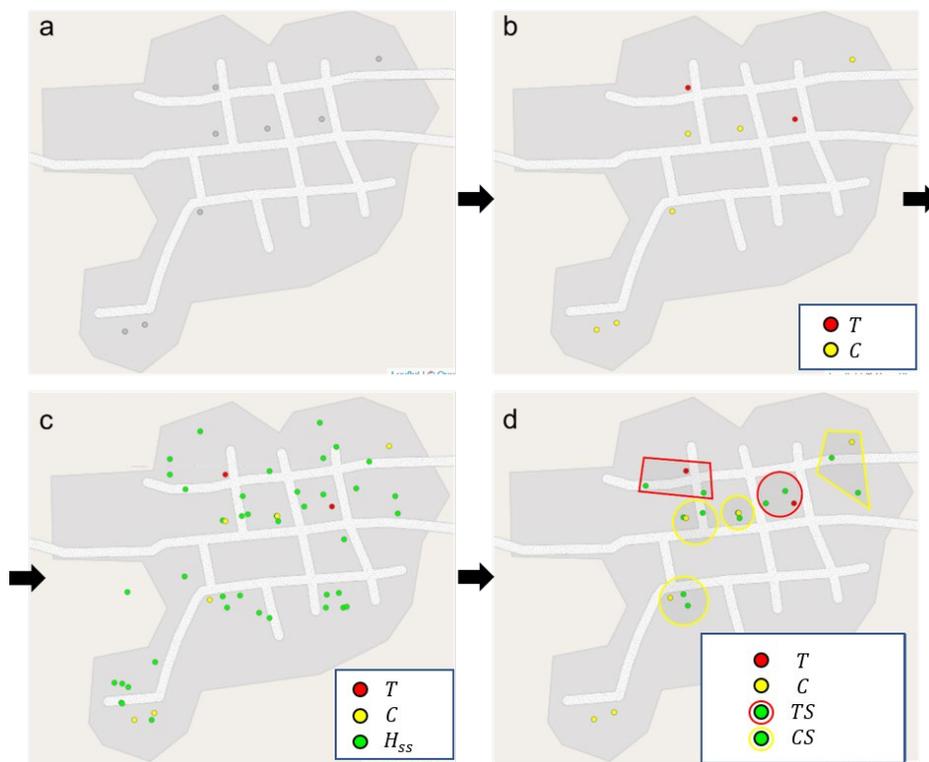
¹³ For more details on how HH_{SS} households have been associated to either T or C households and the average/median distance between T or C and their “neighbors”, we refer to the Appendix D.

Table 1: Endline sample composition

Group	Number of households
Treated – T	300
Control – C	900
Treatment spillover – TS	600
Control spillover – CS	1,200

For an illustration of our sampling framework at baseline and follow-up see Figure 2.

Figure 2: Sampling framework at endline



Note: We start with Panel a, which shows the distribution of the eight households that received a long questionnaire. Among these eight households, as shown in Panel b, two households – red dots – were randomly assigned to the treatment group (T) and received a free d.light s300 solar lamp, while the remaining six households – yellow dots – served as a control group (C). HH_{SS} households are represented in Panel c by green dots. Panel d visually represents the division between CT and CS among select HH_{SS} .

Baseline characteristics of villages and households

Baseline summary statistics between households of the treatment and control group are shown in Table C.1. The table indicates that households of both groups are comparable with respect to socioeconomic characteristics (household head age, gender and education; household size;

wealth) and current energy access (main lighting source; solar lamp ownership and solar energy awareness). Only the difference in the gender of the household head is borderline statistically significant – yet, the respective value of the normalized difference and the joint F-test indicate that this difference is not of economic importance.

Power calculations

Primary Hypotheses:

To measure the direct effects of the provision of a high-quality solar lamp, we focus on the 1,200 long-survey households (HH_{LS} ; $T = 300$ and $C = 900$). We are able to detect a minimum detectable effect (MDE) of 0.2 standard deviations (SD) for an increase in WTP (i.e., demand) for solar lamps or CFA Franc 830, which corresponds to roughly 4.5% of the resale product price of d.light s300 at baseline.

As to the spillover analysis, with 600 TS and 1,200 CS , we will be powered to detect an MDE of 3.5%. Thus, we can detect an even smaller MDE relative to MDE of the direct effect since we expect that spillover effects will likely attenuate from direct effects.

Secondary Hypotheses:

For development outcomes, we are powered to detect an MDE of 0.2 SD (or a reduction of approx. 15% of total energy expenditure, compared to roughly 30% found in Grimm et al. (2017)).

Moreover, the sample size of 20 households per village (totaling 3,000 households) enables us to detect an MDE of the awareness campaign of 7 percentage points in the adoption rate of solar lighting products (i.e., with a total of 50 clusters per arm and an intra-cluster correlation of 11%). When measuring the effects of the interaction between the campaign and the free provision of a high-quality lamp, we are essentially comparing treated households in campaign villages ($N = 100$) with treated households in control villages ($N = 200$). We are able to detect an MDE of 0.35 SD or CFA Franc 1,530 or 8.3 % of the retail price.¹⁴

Data collection and processing

The key data sources are as follows:

1. *Baseline survey* (already conducted) of 7,085 households across 150 villages in the regions of Thiès and Diourbel, which took place in March 2016. More concrete, the sample consist of 1,200 long-survey households and 5,885 short-survey households. This baseline survey was conducted by a local survey company using survey tablets. Surveys were conducted in the local languages of Wolof and Serer. The baseline survey collected

¹⁴ In a robustness test, we will also compare the 50 treatment villages to 50 “pure” control villages (removing the 50 villages where people were only exposed to the radio campaign that was found to be ineffective, Coville et al., 2019). This results in an MDE of 0.4 SD.

socioeconomic characteristics, information on energy access and use, development outcomes, GPS coordinates and follow-up contact information. Table C.1 provides key summary statistics for the long-survey households.

2. *Endline survey*: the follow-up for the endline survey was conducted from January 2024 to mid-March 2024. We revisited all 1,200 long-survey households and a sub-sample of 1,800 short-survey households. The data was collected in person in cooperation with a local survey firm. Surveys were done on tablets with SurveyCTO, including multiple consistency checks such as geo-codes and time-stamps to verify where and when surveys are done. A team member was supervising the data collection as a field coordinator. We established protocols for high-frequency checks, spot checks and back-checks (i.e., random quality control) to ensure proper quality. We administered the endline survey questionnaire to both long- and short-survey households. Moreover, we conducted the BDM exercise for the solar lamp and a solar home system with follow-up questions on perceived quality and intended use of the respective solar lighting products. The BDM exercise with both solar lighting products was done with all 3,000 households at follow-up. Before starting the exercise, field staff was providing a description based on a standardized protocol and started by doing a test with a very low-cost item. Once they were assured that the respondent understands the procedure, enumerators were following through with offering a Tier 1 solar lamp (i.e., the Sunshine 300), as well as the Tier 2 solar home system, and elicit the WTP, accordingly. We randomized the order in which the different technologies were presented. Moreover, participants were informed upfront that they will only be offered one out of the two products for purchase, which will be determined per random draw. Figure E.1 and Figure E.2 in the appendix further illustrate different scenarios of the BDM implementation. The data collection was considered complete once all 1,200 long-survey and all sampled 1,800 short-survey households were interviewed. A lower number for the long-survey household was only to be accepted if the survey firm could provide plausible evidence that households cannot be located (e.g., because of migration). To account for potential attrition among the short-survey households, we include a list of replacement households. For this spillover sample, the third closest HH_{ss} would be considered as the primary replacement household, followed by the fourth closest. Only in the unlikely case that this was not possible, we would have reverted to interviewing additional households not surveyed at baseline.

Variations from the intended sample size

Considering the long follow-up period of eight years, it was reasonable to assume that we would face a problem of attrition. In the baseline survey, we recorded the household GPS data and various telephone numbers to increase the chances of contacting and relocating them for the follow-up.

In consultation with the contracted survey firm, we decided to call ahead of the follow-up survey to inform households about the upcoming survey and take stock of potential changes in residence. Already during this phone survey in October/November 2023, we managed to reach the majority of the households, either directly or through the village head, to confirm that they were still residing in the same village.

During our follow-up survey, we reached 97.5% of the households from the baseline. As anticipated, the low-level of attrition is random. That is, we reached 94.5% of the treated (long-survey) households and 95.2% of the control (long-survey households). Of the sampled spillover (short-survey) households, we reached 98.2%.

Note that we do not always survey the same respondent who was surveyed in the baseline. Given the BDM procedure, we needed a household member with financial decision-making power to respond to the endline survey. Yet, we included a variety of filter questions before starting the interview, to at least ensure that we were interviewing the same household in January/February/March 2024 as in the baseline in March 2016.

Pilot data

The baseline data are summarized in Table C.1. We discuss in Section 4, when outlining our empirical strategy, how the baseline data will be used to achieve more precise estimates. Moreover, the baseline data informed our power calculations described above.

4. Analysis

Statistical methods and models

Primary hypotheses

Hypothesis 1a: Our primary analysis uses the 1,200 long-survey households as observations and outcomes from the endline survey. We will estimate the following linear regression to estimate an intention-to-treat (ITT) effect:

$$(1) WTP_{ivj} = \alpha + \beta T_{iv} + X_{iv}\gamma + \vartheta_v + \epsilon_{iv}$$

Here, WTP_{ivj} is the revealed WTP of household i in village v for technology j , where $j = \{1,2\}$ (i.e., Sunshine 300 and solar home system). T_{iv} is a dummy variable equal to 1 if the household was assigned to receive the treatment, and 0 otherwise. Thus, the coefficient β yields the ITT effects on the demand for Tier 1 and Tier 2 solar energy devices eight years after receiving the d.light s300, respectively. X_{iv} represents a vector of control variables (such as head of household and household socio-economic characteristics, but also baseline variables that proxy for the outcome); we estimate Equation 1 with and without these control variables to explore whether our findings are sensitive to any bias induced by the small imbalances between the treatment and the control group. Moreover, we follow the suggestion of Dizon-Ross and Jayachandran (2022) and another estimation where we add the WTP for a benchmark good (i.e., in our case the WTP for a bar of soap from the test round) as a control variable to improve the accuracy and precision of our measured WTP for solar lighting products.¹⁵ ϑ_v are village fixed effects and ϵ_{iv} indicates the error term. For robustness, we will also estimate Equation 1 with log WTP.

With WTP for both solar energy technologies being one of our main outcome, households that do not provide a WTP will inevitably drop out of our sample. We will deal with large outliers in the WTP measure by winsorizing at a conservative cut-off at the two lower and upper percentiles, and conduct robustness checks without winsorization and with winsorization at the five lower and upper percentiles.

We have to anticipate that the WTP measure may suffer from measurement bias in terms of households over-estimating their true WTP, which would result in them not purchasing the product after a successful bid (“purchase decliners”). Through extensive enumerator training and various comprehension checks with the responded, we aim at minimizing this risk. To account for potentially high rates of purchase declining, will follow Grimm et al. (2020) and provide adjusted estimates of the WTP.¹⁶

¹⁵ We can only include the WTP for the benchmark good, if potential income effects are not stronger among the treatment households, and those translate over to the WTP of the respective benchmark good.

¹⁶ Grimm et al. (2020) themselves follow the approach used in Benyishay and Mobarak (2019).

To probe into the impact on other investments into electricity as an additional outcome for the primary hypothesis, we will replace the WTP-measure in Equation 1 with a variable indicating the electricity tier (ET) to which the household has access Tier

$$(2) ET_{iv} = \alpha + \beta T_{iv} + X_{iv}\gamma + \vartheta_v + \epsilon_{iv}$$

We define ET as a binary outcome that takes the value of 1 either if the household's tier is above the median tier or if the household's tier is equal to 5 (the latter only in case the median tier is 5).

Depending on the results of the three main outcomes (i.e., WTP for both solar lighting products and electricity tier), we will further explore the intensive margin by examining the current average monthly energy consumption (i.e., in form of a continuous variable). We will analyze the intensive margin either among all households (under the premise that e.g. the adoption of grid electricity is evenly distributed among the treatment and control group) or on a conditional sample of households.

Hypothesis 1b: In order to assess spillovers, we will use the short-survey sample and compare the closest neighbors to households that were (randomly) chosen for treatment (receiving a solar lamp for free) to the closest neighbors to households that could have been chosen but were not (i.e., those serving as control households). The key idea behind the identification strategy is that the location of a treated household (red dot in Panel b of Figure 2) is as good as random between candidate locations (grey dots in Panel a of Figure 2). To estimate the spillover effects, we then want to compare individuals near realized treatment locations ("neighbors" to red dots; TS) and individuals near counterfactual (unrealized) candidate locations ("neighbors" to yellow dots; CS).

To estimate spillover effects, we will run the following specifications:

$$(3) WTP_{ivj} = \alpha + \beta TS_{iv} + X_{iv}\gamma + \vartheta_v + \epsilon_{iv}$$

$$(4) ET_{iv} = \alpha + \beta TS_{iv} + X_{iv}\gamma + \vartheta_v + \epsilon_{iv}$$

Here, TS_{iv} is a dummy variable equal to 1 if the household is a close neighbor of a treatment household, and 0 if the household is a close neighbor of a control household (i.e., CS).¹⁷ To account for the fact that some neighbors in our sample are more closely located to the treatment households or counterfactual candidate locations than others, we will additionally introduce a weighting ω_{iv} that corrects for the distance.¹⁸

The approach for missing values and outliers remains the same as described under the first primary hypothesis. As with the long-survey households, we will run Equations 3 and 4 with and without covariates.

¹⁷ We can equally divide C households into TS and CS , and include them in the estimations accordingly.

¹⁸ Short-survey households are inevitably located in the same villages as long-survey households, hence, when analyzing spillover effects, we will also control for the BAC.

Moreover, to descriptively assess the spillover effects, we will ask the treatment households what they used the d.light s300 solar lamp for, where they primarily used it (i.e., outside or inside), who used the lamp (i.e., members within or outside the household) and whether they shared it with friends/family outside their household. Ultimately, the latter part will also be important for identifying whether there are any spillover effects between treatment and control households of the long-survey household sample.

Secondary hypotheses

Hypothesis 2a: For the secondary analysis of development outcomes, we will use the 1,200 long-survey households as observations, outcomes from the endline survey, and where available also outcomes from the baseline survey. To ascertain the long-term ITT impacts of the intervention on development indicators, we will estimate the following linear regression:

$$(5) Y_{iv} = \alpha + \beta T_{iv} + X_{iv}\gamma + \vartheta_v + \epsilon_{iv}$$

Here, Y_{iv} is the development outcome of interest for household i in village v . More specifically, these outcomes include:

- monthly total income (in CFA Franc)
- monthly income from non-farming activities (in CFA Franc)
- monthly total expenditures on energy sources for lighting (in CFA Franc)
- monthly expenditures (in CFA Franc) for:
 - biogas
 - LPG
 - gasoline
 - kerosene/paraffin
 - oil
 - candles
 - firewood
 - dry-cell batteries
 - generators
 - solar energy products
 - grid connection
- whether household runs a non-agricultural or business enterprise within household/compound (binary variable)
- whether household runs a non-agricultural or business enterprise within household/compound that uses electricity (binary variable)
- time spent on domestic work (in minutes) for:
 - household head
 - spouse
 - oldest child
- time spent on income-generating work (in minutes) for:

- household head
- spouse
- oldest child
- time spent on studying (in minutes) for the oldest child enrolled in school:
 - at school at daylight
 - at school after nightfall
 - at home at daylight
 - at home after nightfall

T_{iv} is a dummy variable equal to 1 if the household is assigned to receive the treatment, and 0 otherwise. The remaining variables are the same as in Equation 1. For the outcomes where baseline information is available (i.e., monthly total income; monthly total expenditures on energy sources for lighting; time spent on domestic work, income-generating work and studying for the oldest child), we will revert to an Ancova specification to boost power.

We will minimize item non-response through enumerator training, backchecks, spot checks, and high frequency monitoring. We will deal with large outliers in the monetary (i.e., income and expenditures) and time measures (i.e., time spent on ...) by winsorizing at a conservative cut-off at the two lower and upper percentiles, and conduct robustness checks without winsorization and with winsorization at the five lower and upper percentiles.¹⁹

Hypothesis 2b:

In order to assess whether households exposed to a solar product for a longer time know more about the general functioning of solar lighting products, we will replace the outcome of Equation 1 and use responses to the knowledge questions as alternative outcomes:

$$(6) K_{ivj} = \alpha + \beta T_{iv} + X_{iv}\gamma + \vartheta_v + \epsilon_{iv}$$

The differential knowledge question measure:

- whether the household knows how long it takes on average to charge a solar lamp/solar home system (i.e., binary outcome)
- whether the household knows which devices can be run with a solar lamp/solar home system (i.e., binary outcome)

In order to assess learning effects stemming from households learning about the potential for productive uses (as opposed to pure learning-by-experience effects), we will make use of the additional randomized treatment in the form of BAC with community outreach print materials distributed in 50 villages. Hence, we will compare revealed WTP and electricity tier of treatment

¹⁹ Another method we found useful in other surveys so far is to ask people to enter both the number and write the number down in words. This has proven to give more reliable responses to monetary measures (including WTP).

households located in BAC-treatment villages with treatment households located in BAC-control villages. More precisely, we will estimate an augmented version of Equation 1 as follows:

$$(7) WTP_{ivj} = \alpha + \beta_1 T_{iv} + \beta_2 BAC_v + \beta_3 T_{iv} \times BAC_v + X_{iv}\gamma + \epsilon_{iv},$$

$$(8) ET_{iv} = \alpha + \beta_1 T_{iv} + \beta_2 BAC_v + \beta_3 T_{iv} \times BAC_v + X_{iv}\gamma + \epsilon_{iv},$$

where BAC_v is a dummy variable equal to 1 if village v was assigned to receive the print material BAC-treatment, and 0 otherwise.²⁰ The remaining variables are the same as in the other equations. With the BAC varying at the village level, we will refrain from including village fixed-effects and revert to cross-village comparisons. We cluster standard errors at the village-level. Additionally, we will assess the impact of the solar lamp treatment within a split sample approach for the BAC-control and BAC-treatment group separately.

The approach to missing values and outliers remains the same as described under the primary hypotheses.

Multiple outcome and multiple hypothesis testing

Against the background that we have multiple outcomes of interest in our primary hypotheses – i.e., two different WTP measures and the electricity tier – and we look at heterogenous effects (see next Section), we are testing multiple hypotheses simultaneously. To some extent, we reduce the concerns associated with testing multiple hypothesis with the electricity tier variable, which inherently consists of combining multiple outcomes of energy access to one single index variable. Yet, we further test the robustness of our results with regard to multiple hypotheses testing, we apply the bootstrap-based procedure by List, Shaik and Xu (2019) for the regressions without covariates and List, Shaik and Vayalinkal (2023) for the regression with covariates, and report their adjusted p-values. Hence, we test the families of hypotheses that emerge due to multiple outcomes for the hypotheses *1a* and *1b*, and additionally test the families of hypotheses that emerge due to multiple subgroups. In each case, we will list the respective coefficients with the unadjusted p-value and various adjusted p-values (i.e., the ones estimated with List et al. (2019) and (2023)).

Heterogeneous Effects

We envision additional heterogeneity analysis in the context of our primary hypotheses. The WTP for a solar lamp and/or solar home system may depend on whether the household already owns the respective solar lighting product or whether the household is connected to the grid (see e.g.,

²⁰ We will ascertain the zero impacts of the radio campaign by varying the comparison group, i.e., (i) limit the control group to the pure BAC-control group (excluding villages that were part of the radio BAC-treatment) and (ii) comparing the pure BAC-control group with the radio BAC-treatment group (excluding villages that were part of the combined radio and print material BAC-treatment).

Mekonnen et al. 2023).²¹ Hence, when using WTP as an outcome, we will analyze treatment effects separately for households that already adopted the respective solar lighting product and, additionally, separately for households living in villages connected to the electricity grid (as reported by the village head) . These heterogenous effects will be explored via interaction terms and split samples.

²¹ The direction of the effect of an existing connection to the grid is a-priori not clear. In their review, Kizilcec et al. (2022), for instance, observe that households in Sub-Saharan Africa frequently use solar home systems as a back-up to the electricity grid.

5. Interpreting Results

This study contributes to the growing literature on the impacts of grid and off-grid electrification and attempts to explore reasons for the puzzlingly limited impacts of electricity provision in low- and lower-middle-income countries by understanding whether access to zero-cost electricity induces higher demand for electricity over time. The existing evidence concerning entry-level products allowing basic uses like lighting and cell-phone charging has found consistent reductions in household energy expenditure and mixed impacts in development outcomes in the short-term (Mahajan, Harish, and Urpelainen 2020; Grimm et al. 2017; Hassan and Lucchino 2016; Kudo, Shonchoy, and Takahashi 2019; Aklin et al. 2017; Aevarsdottir, Barton, and Bold 2017; Wagner et al. 2021; Lemaire 2018). We are the first to experimentally study the long-term effects of solar electricity, allowing for the possibility that impacts take time to accumulate. Other related studies have explored the effects of solar access on future electricity demand. These have typically focused on understanding whether subsidized provision may dampen demand for the same product in the future, and whether spillovers in WTP for the same product/service level occur (Meriggi, Bulte, and Mobarak 2021; Yoon, Urpelainen, and Kandlikar 2016). These studies also typically focus on short-term effects ranging from one week to two years.

Against this background, this paper's main contribution is being the first to explore whether access to entry-level solar electricity service moves people up the energy ladder by inducing demand for higher levels of electricity service over time. The eight-year time frame also provides estimates of the longest-term direct and spillover impacts of solar electrification to date. Given the dominance of "least-cost" electrification plans being implemented by governments around the world, evidence on the long-term electricity investment and productive use trajectory of households provided with entry-level service will be a crucial input to developing optimal strategies for future electrification efforts.

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7. Appendices

Appendix A: Main intervention

Figure A.1: d.light s300



Appendix B: Behavioral Awareness Campaign intervention

Figure B.1: BAC flyer



Note: This is an example of the flyers distributed in the BAC-treatment villages. It was translated into one of the four original languages.

Appendix C: Baseline information

Figure C.1: Distribution of villages

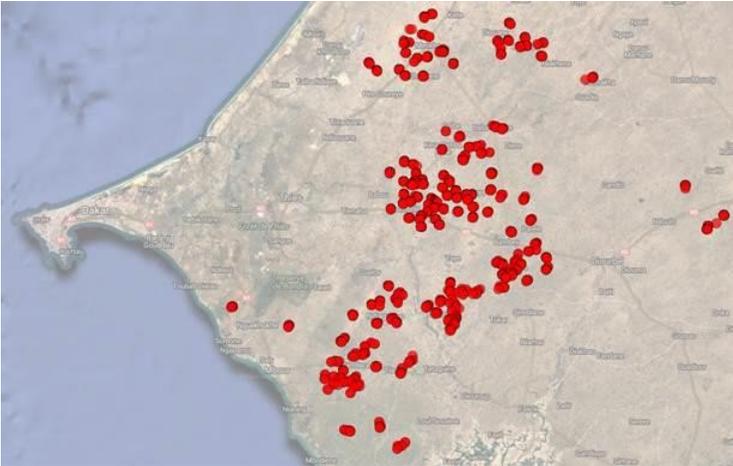


Table C.1: Balance table

	Control (C)		Treatment (T)		C - T		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	SD	Mean	SD	Diff.	p-value	Norm. diff.
Age of HH head (years)	46.1	16.7	45.3	16.1	0.1	0.467	-0.035
HH head is female	0.449		0.505		-0.056	0.095	0.079
HH head: no schooling	0.791		0.796		-0.005	0.851	0.009
HH head: some primary educ.	0.105		0.107		-0.002	0.904	0.006
HH head: completed primary educ.	0.028		0.037		-0.009	0.431	0.036
HH head: some secondary educ.	0.050		0.033		0.017	0.235	-0.059
HH head: completed secondary educ.	0.017		0.007		0.010	0.206	-0.066
HH head: tertiary educ.	0.010		0.020		-0.010	0.176	0.058
HH size (members)	12.6	6.9	12.0	5.8	0.6	0.195	-0.064
No. of children between 6 and 18 years	4.2	3.3	4.2	3.1	0.0	0.961	0.002
Roof is finished	0.949		0.943		0.006	0.703	-0.018
Main lighting source: none	0.001		0.003		-0.002	0.413	0.033
Main lighting source: oil lamp or candles	0.1		0.1		0.0	0.414	0.038
Main lighting source: battery or generator	0.457		0.498		-0.041	0.217	0.058
Main lighting source: grid electricity	0.249		0.221		0.028	0.321	-0.047
Main lighting source: solar energy (lamp or other system)	0.234		0.207		0.026	0.349	-0.045
Main lighting source: other	0.008		0.007		0.001	0.849	-0.009
HH has ever owned a solar lamp	0.365		0.381		-0.016	0.611	0.024
HH has solar lamp	0.315		0.331		-0.016	0.600	0.025
HH head demonstrates basic awareness of solar energy	0.712		0.759		-0.047	0.113	0.076
HH member has visited local market in past 4 weeks	0.814		0.783		0.032	0.231	-0.056
N	899		299				

Note: The table presents balance comparison between households in the control and treatment group. Columns (1) and (3) report the mean values for each group and Columns (2) and (4) report the respective standard deviation to the means. Column (5) shows the difference between the two group means and Column (6) the p-values for the test of equality of means. Column (7) indicates the normalized difference. The joint null of equal means is not rejected at standard levels ($F = 1.396$, $p\text{-value} = 0.137$). One observation within each group is missing.

Appendix D: Spillover effects

Association of T and C households to two closest HH_{ss}

In order to define the closest HH_{ss} households to treated and control households, we proceed as follows.

Within each village, we first consider the two T households (lets denote them as t_i with $i = 1, \dots, 2$) only and calculate the distance between each t_i and each HH_{ssj} with $j = 1, \dots, 40$. We then order the distances and associate pair of t_i and HH_{ssj} in ascending order, as shown in Figure D.1. Figures D.2 and D.3 provide insights into the spatial dispersion of the households in our sample.

In the example displayed in Figure D.1, we can see how the distance between t_1 and HH_{ss2} is the smallest. HH_{ss2} will then be associated with t_1 . Following the same logic, HH_{ss4} will also be associated with t_1 . Now that t_1 has been associated with its two closest neighbors, we turn to t_2 . In the example below, HH_{ss10} , is the closest HH_{ssj} to t_2 and is naturally assigned to the latter. Looking at the rank, the second closest HH_{ssj} to t_2 would be HH_{ss4} , ranked in position 9. However, HH_{ss4} has already been assigned to t_1 , hence, it must be skipped. The third closest is HH_{ss9} , which accordingly gets assigned to t_2 .

Once two HH_{ssj} have been assigned to each t_i , it is time to move to C households (lets denote them as c_k with $k = 1, \dots, 4$). Note that, within each village, we only consider four out of six control households (randomly selected). Following the same logic, every c_k will be associated with two HH_{ssj} . Importantly, HH_{ssj} that have been already assigned to t_i will not be considered as potential candidates to be associated with c_k . The choice of starting by t_i in the assignment of closest neighbors is to assure that HH_{ssj} associated with HH_{ssj} are the closest possible and, hence, have the highest probability of getting exposed to spillovers.

Figure D.1: Example of association of T households to two closest HH_{ss} (within each village)

dist_from	dist_to	dist (m)	rank
t1	HH_{ss2}	36.73	1
t1	HH_{ss4}	52.31	2
t1	HH_{ss1}	53.69	3
t1	HH_{ss8}	56.17	4
t2	HH_{ss10}	57.00	5
t1	HH_{ss5}	62.65	6
t1	HH_{ss3}	64.75	7
t1	HH_{ss6}	83.08	8
t2	HH_{ss4}	83.58	9
t1	HH_{ss7}	84.01	10
t2	HH_{ss9}	86.67	11

dist_from	dist_to	dist (m)	rank
t1	HH_{ss2}	36.73	1
t1	HH_{ss4}	52.31	2
t2	HH_{ss10}	57.00	5
t2	HH_{ss9}	86.67	11

Figure D.2: Distances between treated households and the two closest HH_{SS}

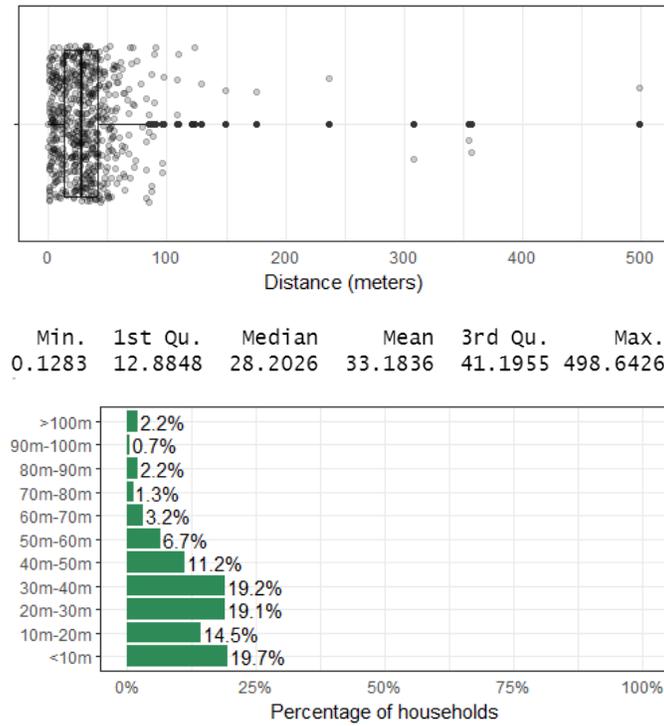
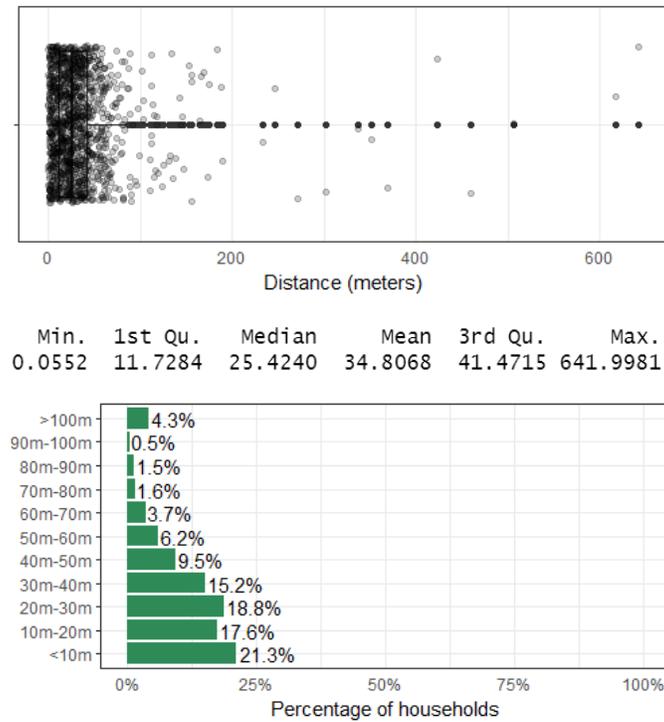


Figure D.3: Distances between control households and the two closest HH_{SS}



Appendix E: BDM exercise

Figure E.1: Graphical example of BDM implementation with product draw, price draw and transaction

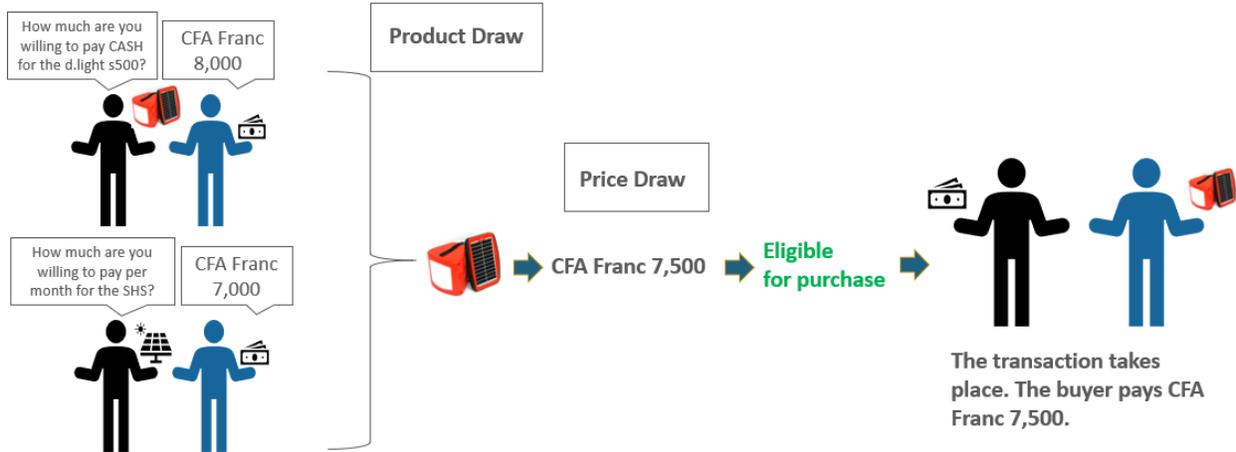


Figure E.2: Graphical example of BDM implementation with product draw, price draw and NO transaction



8. Administrative information

Funding:

This work was supported by the European Commission INTPA impact evaluation fund, the Development Impact Evaluation (DIME) i2i fund through the United Kingdom's Foreign, Commonwealth and Development Office (FCDO) and the World Bank's Lighting Africa trust fund.

Institutional Review Board (ethics approval):

IRB approval for the baseline study was obtained from IRB Solutions (Protocol #2016/03/4, 2016-03-04).

IRB approval for the endline study was obtained by the Ethics Committee of Leibniz University Hannover on 23 June 2023.

Declaration of interest:

The researchers have no relevant or material financial interests that relate to the research described in the paper.

Acknowledgments:

We are grateful to Olivier Gallou and Marco Valenza for excellent field coordination support during the baseline. We acknowledge research assistance from John Dundas and Patricio Boyd. We are grateful to the World Bank Lighting Africa team (Micah Malik, Melissa Basque, Ian Muir, and Daniel Murphy), the Voto Mobile team (Adam Cox, Jocelyn Light, and Levi Goertz) and Total Senegal (Vincent Couvelaere). The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.