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The Effect of Information and Subsidy on Adoption of Solar Lanterns

An Application of the BDM Bidding Mechanism in Rural Ethiopia

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Abstract

Renewable energy sources such as solar are an alternative to provide clean lighting for many rural households in developing countries. However, transition to these lighting sources has been slow. Using the Becker-Degroot-Marschak (BDM) bidding mechanism and a randomized field experiment, this study investigated the effect of information and subsidy policy instruments on the uptake of solar lanterns. Unlike most previous studies on solar technologies, we use a more comprehensive and more transparent approach in the elicitation of willingness to pay (WTP) using the BDM method, as our random draw is from a wide range of uniformly distributed prices, drawn in front of the subjects. We found that an increase in the amount of subsidy, accounted for in the prices, increases the adoption rate. Provision of information about the private and public benefits of the solar lantern increases adoption only when it is combined with a high level of subsidies. Households with access to grid electricity are less likely to adopt and have a lower willingness to pay, while those using kerosene as a source of lighting are more likely to adopt. We also find that access to credit increases willingness to pay. The results suggest that the related UN Sustainable Development Goals (SDGs) and Sustainable Energy for All (SEforAll) goal of universal electricity access may not be achieved without subsidizing such solar lanterns.

Keywords: renewable energy, Ethiopia, solar lanterns, information, subsidy, market-based and non-market policy instruments

JEL Codes: D10, Q40, Q41

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1. Introduction

About 620 million people in sub-Saharan Africa do not have access to electricity services. Because grid electricity is capital intensive and takes more time and resources to reach rural households, especially for dispersed settlements, off-grid electricity sources such as solar lanterns are alternatives to reach the rural poor living in remote areas, and to achieve goals of universal electrification. Notwithstanding its advantages, penetration of off-grid electricity is very limited.

Households' reliance on biomass and kerosene for cooking and lighting creates serious health risks and imposes a significant economic burden in terms of the monetary and time costs of purchasing or gathering the fuel sources (Rom and Gunther, 2018). These patterns of household fuel use also add to the global accumulation of greenhouse gas emissions, through forest degradation, fossil fuel combustion with the use of kerosene, and black carbon emissions, among others. Thus, transition to renewable energy is important for the well-being of people in developing countries in particular and the world in general. However, recent studies in rural Africa have found that, while off-grid solar is the preferable option to reach mass electrification, poor households' willingness to pay for this energy source is less than cost-covering prices (Grimm et al., 2020).

In Ethiopia, where this study is conducted, the use of renewable energy in urban areas, which constitute about 20% of the total population, is increasing, but the overwhelming majority of rural households continue to rely on biomass and kerosene as fuel sources for cooking and lighting. Further, while urbanization is rapidly increasing, the majority of Ethiopians will remain in rural areas for some time to come. This pattern of energy consumption in Ethiopia, which is similar to most sub-Saharan African countries, needs to change if the energy sector is to become sustainable.

Households face costs in shifting to renewable energy sources, including the need to acquire and become familiar with the use of different equipment. Monetary costs impede adoption by low-income households, even when the individual household benefits are fully understood. Households also may not account for global externalities (such as climate change) in their purchase decisions, and they may not fully internalize the private benefits (including reduced health risks), partly because of lack of information about such benefits. Thus, policymakers are faced with the need to design and implement cost-effective policy instruments to promote the uptake and usage of renewable technologies. Non-market-based policy instruments (e.g., information and regulation), as well as market-based instruments (e.g., prices, taxes and subsidies), can be used to promote households' use of renewable energy sources.

Policies to provide monetary incentives are expensive from a budgetary perspective, and they may not assure the actual uptake of the technology by targeted households, given informational constraints and inertia due to customs and traditions (Ang et al., 2020).

Non-price motivations, on the other hand, have played an increasingly important role during the last decade in efforts to accelerate adoption of renewable energy technologies. Experiments with non-market-based instruments have focused mainly on information provision, so that individuals become aware not only of the more direct and immediate benefits of the adoption of a given good (or technology or behavior), but also the indirect benefits such as the economic and environmental consequences of their actions. Based on the premise that household-level behavioral changes could lead to energy transitions, non-market-based instruments can be used in combination with market-based instruments to increase the adoption of renewable energy technologies.

Our review of studies that examine the effects of market-based and non-market policy instruments (e.g., Alem et al., 2017; Bernedo et al., 2014; Allcott and Rogers, 2014; Ito et al., 2015; Asensio and Delmas, 2015; Meriggi et al., 2017; Rom and Gunther, 2018; Grimm et al., 2020) suggests a lack of comparisons of these instruments. Studies that examine the role of providing information on private and environmental benefits are also limited.

Using a randomized experiment and Becker-Degroot-Marschak (BDM) willingness to pay (WTP) elicitation methods,[1] this study aims at investigating the effectiveness of both information provision and subsidies for adoption of and willingness to pay for solar lanterns for residential lighting in rural Ethiopia.

The intervention consists of the provision of information (including monetary savings, health benefits and environmental benefits) in order to incentivize the adoption of a solar lantern. Unlike most previous studies on adoption of solar technologies that used the BDM method for WTP elicitation (Meriggi et al., 2017, Rom and Gunther, 2018), this paper uses a wide range of uniformly distributed prices that are truly randomly chosen; in addition, the random draw was done in front of the subjects, which increases the transparency of the process. Using the BDM mechanism and comparing price and non-price policy instruments, the study also contributes by adding evidence on adoption of off-grid technology in Ethiopia and by expanding the growing but limited literature on the interplay between price and non-price policy instruments.

[1] The BDM bidding mechanism helps elicit the true willingness to pay of subjects in an experiment which is incentive compatible because subjects will not benefit by overstating or understating their willingness to pay. For details please see the discussion in the section on experimental design.

We found that as expected, an increase in the amount of subsidy increases the adoption rate. However, provision of information about the private and public benefits of the solar lantern alone did not have a significant effect on adoption rate and willingness to pay. Combining information with subsidies increases adoption only when the subsidy levels are high. Most of the households would purchase the solar lantern under study only if it were subsidized, suggesting that the UN Sustainable Development Goal (SDG) and the related Sustainable Energy for All (SEforAll) goal of universal electricity access may not be achieved without subsidizing even relatively lower-cost off-grid technologies. We also found that a household's connection to the grid decreases adoption of and willingness to pay for the solar lantern, suggesting that grid electricity is a preferred source of lighting. Conversely, the use of kerosene for lighting increases adoption of the solar lantern, suggesting kerosene is a less preferred lighting source. Access to credit increases willingness to pay by relaxing liquidity constraints faced by the respondents. Our results have implications for the importance of market-based and non-market-based policy instruments to enhance the diffusion of solar lanterns in rural Ethiopia.

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature on the role of market-based and non-market based (information) policy instruments to influence pro-environmental behavior such as adoption of renewable energy technologies. In section 3, we discuss data, sampling strategy, experimental design and empirical strategy. In sections 4 and 5, we present a discussion of the descriptive and econometric results, respectively. Section 6 presents the main conclusions and policy recommendations.

2. Review of Literature

In this section, we present a review of studies on the roles of information and market-based policy instruments in addressing environmental problems.

2.1 Information Provision as a Policy Instrument to Address Environmental Problems

In the last couple of decades, there has been a growing trend of using information provision as a policy instrument (Sterner and Coria, 2012). Information provision attempts to influence people through transfer of knowledge, communication of reasoned arguments, and moral suasion to achieve a policy goal (Vedung and van der Doelen, 1998). The content could take the form of pure information (i.e., basic knowledge to understand a problem), normative information (i.e., how the problem is handled by others, and/or measures that are needed to tackle the problem) or argumentative information (i.e., reasons why these measures ought to be undertaken).

Previous studies have shown that non-price incentives for conservation behavior — in the water and electricity domains — can generate notable effects in water or energy consumption through providing individuals with savings tips, historical usage, real time energy usage, and peer comparisons (Jaime and Carlsson, 2018; Alem et al., 2017; Bernedo et al., 2014; Allcott and Rogers, 2014; Ito et al., 2015; Ferraro and Price, 2013; Costa and Kahn, 2013; Ayres et al., 2013; Smith and Visser, 2013; Mizobuchi and Takeuchi, 2012; Ferraro et al., 2011; Allcott, 2011; Vining and Ebreo, 2002; Abrahamse et al., 2005; Fischer, 2008; Asensio and Delmas, 2015; Allcott and Mullainathan, 2010; Chetty, 2015). In the water domain, Bernedo et al. (2014) use a randomized experimental design with over 100,000 households to study the longer-term impacts of a one-time behavioral nudge that aimed to induce voluntary reductions in water use during a drought, where they find the nudge has a surprisingly persistent effect. There is also evidence that normative messages in the form of social comparisons have a greater influence on behavior than simple pro-social messages or technical information alone (see, e.g., Jaime and Carlsson, 2018; Ferraro and Price, 2013; Ferraro et al., 2011). In the electricity domain, Allcott and Rogers (2014) evaluate the short- and long-run effects of a series of programs to send Home Energy Report letters to residential utility customers in the United States comparing their electricity use to that of their neighbors. They find that the average program reduces energy consumption by 2.0%, which provides additional evidence on the effectiveness of non-price interventions. Similar effects were found in Allcott (2011) when focusing on a particular program, while Ayres et al. (2013) find that peer comparisons on home electricity and natural gas usage can lead to reduction in energy consumption of about 1.2% to 2.1%. Gillingham and Tsvetanov (2017) use a randomized controlled experiment to investigate the effects of information provision on home energy audit uptake and find that a message to consumers combining the effects of social norms and salience improves audit uptake by 20 percent.

Evidence also suggests that people exhibit heterogeneous responses when they are provided with information, with changes in behavior driven by observable characteristics such as ideology. For instance, Costa and Kahn (2013) find that liberal and environmentalist households have a more energy-efficient baseline than conservative households, and they are also more responsive to home energy reports, suggesting that factors in addition to private costs may be salient in consumer decision-making. Other studies show that individuals who are less responsive to monetary incentives (i.e., wealthier households and high users of the resource) exhibit significant changes in behavior when they are targeted by information campaigns including a combination of technical information, moral suasion and social comparisons (Jaime and Carlsson, 2018; Ferraro and Miranda, 2013). There is also evidence of rebound effects in interventions of this sort, as pointed out by Byrne et al. (2014), where consumers underestimated their baseline energy consumption. In contrast, there is little evidence of heterogeneous responses to purely technical information or moral suasion (Ferraro and Miranda, 2013).

Although policies of this sort have been mostly in place in developed countries, there is also some evidence that information policies have led to notable changes in behavior in developing countries, generating not only direct effects on the targeted individuals but also indirect effects on individuals who are socially connected with those that have been targeted (Jaime and Carlsson, 2018), or among targeted individuals across consumption domains (Carlsson et al., 2020). Other studies in the context of developing countries are those of Smith and Visser (2013) and Sudarshan (2017), but overall evidence is rather limited.

Other studies have shown that people react differently to the content of information they have been provided. For instance, Asensio and Delmas (2015) find that environment and health-based information strategies outperform monetary saving information to drive energy conservation based on a randomized controlled experiment in the United States and that these information strategies are particularly effective for families with children. Although the content and administration of the information varies to a great extent in the empirical evidence, a study of previous campaigns indicates that the most successful feedback requires a combination of frequency, a long time span of provision, appliance-specific breakdown, presentation of content in a clear and appealing way, and the use of computerized and interactive tools whenever possible (Fischer, 2008). Unlike this literature, studies of non-pecuniary incentives for water/energy conservation behavior are mainly based on cost-based and norm-based information, while other forms of information strategies (e.g., environment and health-based information strategies) are rare.

Finally, in spite of the vast evidence on the effectiveness of information policy, this instrument could lose its effectiveness if it is applied in situations where universal compliance is needed. This is because it relies on voluntary action (i.e., people decide whether to change their behavior). Consequently, as stated by the theory of coinciding interest, this instrument can perform well only when the desired actions are both in the private interest of the economic agents and in the public interest of the regulator (Vedung and van der Doelen, 1998).

2.2 Information Policy and Willingness to Pay for Environmentally Friendly Products

Because individuals consider relevant available information in their decision-making process, information is one of the determinants of an individual's reservation price. There is a vast literature analyzing the effects of information provision on individuals' willingness to pay for consumption goods in several domains. For instance, Oparinde et al. (2016) estimate the effect of nutrition information campaigns and the nature of planting material delivery institutions on consumer demand for biofortified yellow cassava varieties in two states of Nigeria. Consumer demand was estimated using the BDM mechanism. Results indicate that nutrition information results in a large and significant price premium in both states, whereas the nature of the delivery institution has no significant effect. In the health domain, Rousu et al. (2011) estimate the value of counter-marketing information aimed at countering tobacco company claims about the health benefits of reduced-risk cigarettes. By using data from experimental auctions, the authors find no effect of counter-marketing information on smokers' purchasing behavior when individuals are not exposed to marketing information. However, for individuals who are presented with both tobacco company information and counter-marketing information, there is a significant average value per smoker of 8.5 cents per pack. Similarly, Monchuk et al. (2003) find that consumers who are presented with even a small amount of information are more likely to prefer low-nicotine cigarettes. This effect is especially important for individuals who want to quit smoking, compared with hard-core smokers.

As for the demand for environmentally friendly products, Bougherara and Combris (2009) investigate whether information about an eco-labelled product (i.e., its limited private benefits relative to its social benefits) generates an effect on the willingness to pay of individuals. Findings indicate that information does not affect buying prices, suggesting that consumers' willingness to pay for the eco-labelled product is not entirely explained by the attributes generating private benefits, but rather from altruistic motives. Thus, information policy can also be used to incentivize the adoption of or willingness to pay for environmentally friendly technologies. An example is Alem et al. (2017), who investigate the effects of information and social networks on the acquisition of solar lanterns in a non-electrified part of Uttar Pradesh, India. The program consisted of giving solar lanterns to randomly selected "seed" households, and then offering friends of these households the chance to purchase the lantern after some of the friends were given presentations on the lanterns by the seed households. Willingness to pay for the lantern was increased by virtue of contact with a seed household, but it was higher still with the information treatment.

2.3 Roles of Market-based Policy Instruments

Pecuniary policy instruments such as prices, taxes and subsidies may also be used to motivate households to reduce their consumption of electricity or to incentivize the use of renewable energy technologies such as solar. The most commonly studied pecuniary measure is charging consumers different prices for electricity usage during different time periods (e.g., Bartusch et al., 2011; Filippini, 2011; Wolak, 2011). Bartusch et al. (2011) studied the impact of an introduction of a demand-based time-of-use tariff in Sweden. They find that total electricity consumption declined by 11.1 percent and consumption shifted from peak-time to off-peak time. Filippini (2011) also finds that time-differentiated prices can provide an economic incentive to customers so that they can shift electricity consumption from peak to off-peak periods. From a dynamic pricing experiment, Wolak (2011) finds that for both regular and all-electric customers, the percentage demand reduction associated with a given percentage increase in the hourly price is approximately equal to the percentage demand reduction associated with the same percentage price increase of a much longer duration. The evidence on the effect of pecuniary incentives on the adoption of residential renewable energy technologies is still rare. Grimm et al. (2016) examine uptake and impacts of a very small household photovoltaic (PV) kit in rural Rwanda, where they find several economic and environmental impacts, only parts of which are likely to be internalized by households themselves. Their data also show that adoption is impeded by affordability, suggesting that policy would have to consider direct promotion strategies such as subsidies or financing schemes. Bensch et al. (2016) have a more positive finding in Burkina Faso, given the availability of well-performing and less costly unbranded devices. Other studies such as Meriggi et al. (2017), Rom and Gunther (2018), and Grimm et al. (2020) also provide additional evidence on the role of prices or subsidies in adoption of solar lighting technologies. Grimm et al. (2020) find that households' willingness to pay for solar technologies in rural Rwanda is less than cost-covering prices.

2.4 Effects of Information and Market-based Policy Instruments Combined

Most of the studies on energy/water conservation behavior focus on the effects of pecuniary or non-pecuniary policy alone, and there is lack of comparison of pecuniary (price) vs. non-pecuniary (non-price) experiments, especially for the developing world. Sudarshan (2017) provides evidence from India using a randomized control trial in conjunction with a quasi-experiment and finds that replicating the mean effect of the information nudge in electricity consumption through tariff changes alone would require at least a 12.5 percent increase in the price. Comparing these policy instruments can shed light on the debate about what best motivates households' uptake of renewable energy and energy conservation behavior.

3. Methodology

3.1 Baseline Data

Baseline data was collected from a survey of a stratified random sample of 810 rural households from 45 study sites in Ethiopia. Sites were selected purposively from the three largest regional states of Ethiopia (Amhara, Oromia and Southern Nations, Nationalities and Peoples (SNNP) regional states) to maintain heterogeneity in site characteristics while also targeting sites that are not connected to the grid and not targeted by governmental and non-governmental organizations for dissemination of solar lanterns. There were 18 randomly selected households in each of the 45 sites. As noted in the experimental design section below, all 810 households were subjected to the randomized field experiment.

To gather information about observable characteristics of our sample households, we also conducted a baseline survey including: (1) socioeconomic characteristics (including demographic characteristics and wealth), (2) fuel used by households for lighting and the corresponding equipment, (3) knowledge and perceptions of the environmental, health and other effects of using biomass and solar lanterns, and (4) social networks. As the survey was applied to a random sample of households in our study sites, interviewed households will be regarded as our experimental population.

3.2 Experimental Design

After we collected data on baseline characteristics of households, we conducted an information provision experiment to promote the adoption of solar lanterns. This was followed by elicitation of the individuals' WTP using the BDM bidding method. The incentive-compatibility of the method leads us to believe that their stated WTP is a very good approximation of their actual WTP. The following is a summary of our experimental design.

First, we provided information as follows. Interviewed individuals in each village were randomly divided into two groups (treatment and control groups) and placed in two separate rooms. Each group consisted of 9 respondents. The treatment group was provided information on the private and environmental benefits of the solar lantern, which might not be obtained from retailers if a person decides to buy it from the market. The control group did not receive such information (see Appendix 4 for information provided to the treatment group). Each group also received standard information on how the solar lantern is operated and charged and other general information; this standard information, which was given to both groups, can be obtained from retailers if a person decides to buy the item on his/her own from the market. The information we provided describes the amount of money and time buyers can save, brighter light provided compared with using kerosene, and health and the environmental benefits when shifting from other energy sources such as kerosene and wood to solar lanterns. The solar lantern we used for the study is the “Sun-king Pico” with a built-in solar panel (Figure 1). This solar lantern has three light modes (turbo mode with 25 lumens for 6 hours, normal mode with 13 lumens for 12 hours, and low power mode with 2 lumens for 72 hours). It is handheld and hangable with 360 degrees tilt; 3 times brighter than a kerosene lamp, with 5 years of battery life and 2 years warranty. The selling price of the solar lantern at the time of the survey was Birr 245 (about USD 8.75).

Figure 1. The Solar Lantern used (Sun-king Pico)

Note: Front view (left) and back view (right)

Second, after the information provision experiment, in each room we elicited WTP using the BDM bidding method. Before respondents stated their maximum WTP for the solar lantern, we informed them about the decision mechanism underlying the BDM bidding method. Participants were told the range of prices used (i.e., the minimum and the maximum) in the experiment and then were asked individually to bid a price for the solar lantern by stating their maximum willingness to pay. At the end, both groups (treatment and control) were gathered in one place and a random price was selected from a bucket containing a range of uniformly distributed prices. The prices ranged from 20 Birr to 250 Birr with an interval of 10 Birr between each price.[2] The highest price, 250 Birr, was 5 Birr higher than the market price of the solar lantern at the time of the survey. All prices except the highest price reflected a subsidy relative to the market price, but the fact that the price list included a subsidy was not announced to the participants. The purchasers of the solar lantern would pay the randomly drawn price, not their WTP.

Under the above procedures, it would be in the best interest of the participants to bid according to their actual valuation of the solar lantern. This was explained to the respondents until we made sure it was understood. If a respondent's stated WTP was below their actual WTP and a price higher than their stated WTP but not more than their actual WTP was drawn, they would not be allowed to buy the solar lantern, even if they wanted to buy it at this randomly drawn price. On the other hand, if their stated WTP was higher than their actual WTP and the randomly drawn price was higher than their actual WTP and not more than their stated WTP, they would be expected to buy the solar lantern even if they did not want to. Neither of these outcomes is in the best interest of the respondent. Individuals were also informed that if their stated willingness to pay was greater than or equal to the randomly drawn price, they would be given the opportunity to purchase the solar lantern at the randomly drawn price. Payment could be made immediately or after about a month. In cases where a household decided to purchase the solar lantern immediately, the household paid and received the solar lantern immediately. Individuals who wanted to pay later were visited by supervisors after about a month, and the solar lantern was delivered immediately after the individuals made the payment.

After explaining the BDM mechanism, each member of the group was asked individually to state his/her WTP for the solar lantern. At this stage, communication between members in each group was prohibited. Then, the two groups came together in one room where a price was randomly drawn. The randomly drawn price was the same for all households in a study site. This helps to avoid potential spillover effects as well as ethical issues and the related confusion that may arise if different prices apply to different households in the same site. Figure 2 shows the experimental design for a village.

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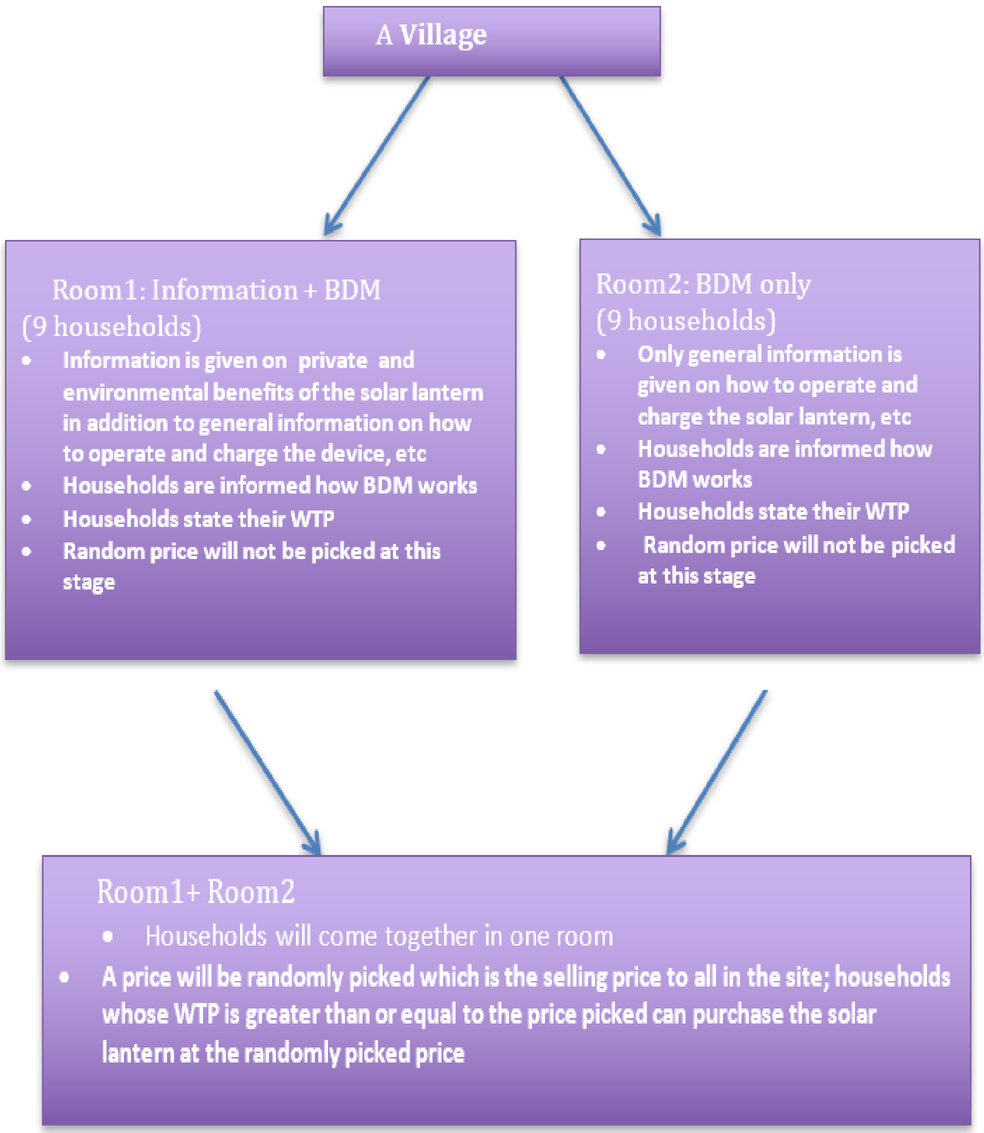
[2] The exchange rate at the time of the survey was 1 USD = 28 Birr. This implies that the range of 20 to 250 Birr is about 0.7 to 8.9 USD. The price interval of 10 Birr (about 36 US cents) is quite small. The 10 Birr interval was chosen because respondents' WTP was expected to typically be in multiples of ten. This is also confirmed by the distribution of WTP data we collected from this study, in which all respondents provided their responses in multiples of ten, except 7 of the 808 respondents, whose WTP was in multiples of 5. We also note that, while the maximum price of 250 in the range is more or less the same as the market price of the solar lantern, the minimum price of 20 Birr was chosen with the expectation that households may typically have a WTP of 20 or more; this is also confirmed by the results of the study, which show that only 5 of the 808 respondents had WTP of less than 20.

Figure 2. Experimental Design



An illustration of our experimental design followed in our intervention is presented as follows, taking a village as an example. Households within a village/site/cluster are randomly assigned as BDM with information group (say, group 1) and BDM without information group (say, group 2). These two groups were placed in separate rooms (e.g., group 1 in room 1 and group 2 in room 2). Group 1 (our treatment group) received information on benefits of the solar lantern while group 2 did not. Otherwise, both groups received the same general information such as how the solar lantern is operated and charged and how the BDM bidding method works.

Each member of the group then stated his/her household's WTP for the solar lantern individually while in the assigned room. After each respondent stated his/her WTP, the two groups came together and a price was randomly selected in front of the respondents from a range of prices that are uniformly distributed (between 20 Birr and 250 Birr with an interval of 10 Birr). This feature of our design differs importantly from most previous studies that used a few prices (typically only three or four different prices) which were determined before the fieldworkers went to the study sites.[3] In our study, the randomly selected price became the selling price for all households within a study site/village. Also, the same individuals were used for both information provision and subsidy/price aspects of the study, which allows us to evaluate and compare individual responses to both non-monetary and monetary incentives.

3.3 Empirical Strategy

Since the allocation of individuals to treatment (information) and control groups is purely random, regression analysis of the effect of provision of information on the adoption of the solar lantern is causal.

We define adoption of the solar lantern, a dependent variable, as a binary variable, which takes a value of one if the household (respondent) purchased the solar lantern based on the BDM bidding method and takes a value of zero otherwise. Because the BDM mechanism generates different random prices at different villages, the effect of these prices on adoption is as good as a village-level random allocation of the prices. The effect of the information may not be the same across the different prices. We expect that informed households with subsidized prices are more likely to adopt than uninformed households with subsidized prices. To capture the combined effect of information and prices, we introduced an interaction term in our regression as in Equation 1.

$$Adoption_{ij} = \alpha + \beta_1 inf_i + \beta_2 Price_j + \beta_3 (inf_i \; x \; Price_j) + X_i \lambda + \varepsilon_{ij} \quad (1)$$

[3] In our study, in each village studied, we picked a price at random from a uniform distribution of 24 different prices. The minimum price in the distribution (20 Birr) is only about 8% of the market price of the solar lantern, while the maximum price (250 Birr) is about 2% higher than the market price. The price interval of 10 Birr is expected to help include most of the possible prices that the respondents would state as there may be a tendency to think in terms of tens in this context. So, we believe this is truly random and the random draw in front of the subjects increases the transparency of the process, unlike previous studies which used a total of less than 5 different prices to randomly choose from and determined those prices ahead of the site visit. Additional advantages of our approach are that we can also consider different levels of subsidy in our analysis given the wide range of prices used in the experiment. We thank Fredrik Carlsson and Francisco Alpízar for suggesting this approach in the design.

where *inf* is a dummy variable taking a value of one if the respondent *i* is part of the information treatment group and zero otherwise, and price is a continuous variable which represents the randomly drawn price of the solar lantern in site/village j. When using the BDM method, prices are randomly drawn from a distribution (in this case a uniform distribution) which is unknown to the participants (buyers). X_i is household's socio-economic characteristics, and e_i is the error term.

Because the price variable in Equation 1 is continuous, we cannot clearly see the effect of different subsidy levels on adoption. We express the subsidy as a percentage of the market price of the solar lantern. For this reason, we consider an alternative by generating three binary prices (i.e., price with 25% subsidy or less, price with subsidy between 25% and 50% and price with subsidy between 50% and 75%) and investigate whether the effect of the three price categories is different. This also allows us to evaluate whether effects of the different prices differ between individuals who received information and those who did not. This is shown in Equation 2.

$$Adoption_{ij} = \alpha + \beta_1 \, inf_i + \beta_2 P_{<25\%} + \beta_3 \, P_{25-50\%} + \beta_4 \, P_{50-75\%} + \beta_5 \, (inf_i \, xP_{<25\%}) + \beta_6 (inf_i \, xP_{25-50\%}) + \beta_7 \, (inf_i \, xP_{50-75\%}) + X_i \lambda + \varepsilon_{ij} \quad (2)$$

where $P_{<25\%}$ is a dummy variable taking the value 1 if the price of the solar lantern in the village is with 25% subsidy or less including full price and 0 otherwise, $P_{25-50\%}$ is a dummy variable taking the value 1 if the price of the solar lantern in the village is between 25% and 50% subsidy and $P_{50-75\%}$ is 1 if the price is between 50% and 75% subsidy. The price with more than 75% subsidy is the base category. This classification of price categories is necessitated by the nature of the experimental design where we considered a range of 24 different prices. As noted, this is unlike most previous studies which use only three or four different prices from which a price is randomly drawn for a site; these previous studies often refer to a particular subsidy level in their analysis, such as 25% subsidy, because the probability that this price will be picked from a range of three or four different prices is very high (e.g., 33.3% if only three prices are used). In these studies, the decision on which site receives which price is made before the fieldworkers go to the sites to conduct the study. However, in our case this approach would typically give us a very small percentage of subjects for whom this particular price is randomly picked, considering that the probability of this happening is very low due to a wide range of different prices considered (about 1 in 24 or less than 5%). The rest of the variables in Equation 2 are as defined in Equation 1.

In addition to the effect of information and subsidy on adoption of the solar lantern, we also study the effect of information on households' WTP for the solar lantern. This can be analyzed using Equation 3.

$$WTP_i = \delta + \theta \inf_i + X_i \gamma + u_i \qquad (3)$$

where WTP is willingness to pay obtained from the BDM, X_i is household socio-economic characteristics and u_i is the error term.

In Equations 1-2 above, the parameters $\beta's$ capture the effect of providing information and/or prices on adoption of the solar lantern. We expect the coefficients of the information variable in each model to be positive because households may not adopt this product if they are not fully aware of its full benefits (i.e., both the private and environmental benefits). We expect the coefficients of price variables in both equations to be positive because households are more likely to buy if the amount of subsidy is larger (or if the price is lower). Likewise, the parameter θ in Equation 3 captures the effect of information on WTP and it is expected to be positive because those who got information on private and environmental benefits of solar lanterns are expected to have a higher WTP. Moreover, parameters λ and γ capture the effect of socio-economic variables on adoption of, and WTP for, the solar lantern, respectively; and α and δ are constant terms.

Because one of our dependent variables in Equations 1 and 2 is binary, non-linear models such as logit and probit are the most commonly used methods of estimation. However, when one or more interaction terms are involved in these models, computation of marginal effect from these non-linear models involves practical difficulty and cannot be interpreted easily.[4] Instead, we used a linear probability model (LPM) because the coefficients are easy to interpret and marginal effects are easy to compute. In fact, Angrist and Pischke (2010) documented that OLS estimates of LPM produce coefficients that are mostly statistically indistinguishable from the marginal effects of the probit model. Moreover, because our measure of the individuals' WTP is non-negative and only three respondents stated a zero willingness to pay, we use the OLS method to estimate the effect of information provision on WTP that was gathered through the BDM bidding method.

[4]Although there is an "inteff" Stata command to estimate the "marginal effect" of interaction effects, this command does not produce the marginal effect of the main variables taking the interaction into account.

4. Descriptive Statistics

This section discusses the descriptive statistics of the outcome variables, treatment variables and key socio-economic characteristics of the households in our study. Table 1 presents descriptive statistics of key socio-economic characteristics of the households considered in our study for the overall sample as well as for treatment and control groups.

As shown in Table 1, on average about 61% and 58% of the information treatment and control households, respectively, used kerosene as the main source of light in their house. This means the majority of households in both the treatment and control group use a dirty fuel source for lighting in their homes. In terms of use of clean lighting energy sources, about 11% and 12% of the treatment and control households, respectively, used solar, and 2.7% and 1.5% of the treatment and control households are connected to grid electricity. This is consistent with previous national level data on rural households' access to off-grid electricity. For example, in the World Bank's MTF survey for Ethiopia, about 11% of households in Ethiopia get electricity access through off-grid electricity sources mainly through solar technologies (MoWIE, 2019).

Table 1. Summary Statistics

Variables	**Description**	**Overall mean**	**Treatment Group**	**Control group**	**(1) - (2)**	**p-value**
Household characteristics			(1)	(2)	(3)	(4)
Age	Age of household head in years	46.866	45.800	48.094	-2.294	0.013
		(0.460)	(0.650)	(0.656)	(0.923)	
Gender of head	Sex of head (1if male)	0.931	0.923	0.938	-0.015	0.407
		(0.009)	(0.013)	(0.012)	(0.018)	
Education	Education level of head in years	2.855	3.099	2.610	0.488	0.029
		(0.112)	(0.167)	(0.148)	(0.223)	
Household size	Household size	5.781	5.768	5.794	-0.026	0.855
		(0.071)	(0.100)	(0.102)	(0.143)	
Wealth measures						
Asset Value	Total asset value in 000 Birr	90	86	93	-7	0.518
		(59.882)	(54.909)	(10.139)	(11.713)	
House ownership	Own house (1 if yes)	0.998	0.995	1.000	-0.005	0.157
		(0.002)	(0.003)	(0.000)	(0.003)	
Rooms	Number of rooms in the house	2.388	2.404	2.368	0.037	0.500

		(0.027)	(0.037)	(0.039)	(0.054)	
Separate kitchen	Separate kitchen (1 if yes)	0.764	0.764	0.760	0.004	0.900
		(0.015)	(0.021)	(0.021)	(0.030)	
Thatched roof	House has thatched roof (1 if yes)	0.226	0.222	0.232	-0.010	0.738
		(0.015)	(0.021)	(0.021)	(0.029)	
Galvanized iron roof	House has galvanized iron roof (1 if yes)	0.755	0.756	0.753	0.002	0.935
		(0.015)	(0.021)	(0.021)	(0.030)	
Energy features						
Rechargeable lump battery	Use of rechargeable lump battery for lighting	0.837	0.827	0.846	-0.019	0.466
		(0.013)	(0.019)	(0.018)	(0.026)	
Kerosene	Use of kerosene for lighting (1 if yes)	0.594)	0.612	0.576	0.0370	0.29
		(0.491)	(0.024)	(0.024)	(0.035)	
Solar energy	Use of solar panel for lighting (1 if yes)	0.121	0.114`	0.129	-0.015	0.502
		(0.011)	(0.016)	(0.017)	(0.023)	
Village grid access	Village access to grid (1 if yes)	0.178	0.175	0.180	-0.005	0.854
		(0.013)	(0.019)	(0.019)	(0.027)	
Connected to grid	Household connected to grid (1 if yes)	0.020	0.027	0.015	0.012	0.221
		(0.005)	(0.008)	(0.006)	(0.010)	
Expenditure for lighting	Monthly expenditure for lighting in Birr	279.471	288.144	270.754	17.390	0.514
		(13.299)	(18.721)	(18.908)	(26.608)	
N	Total number of households	808	405	403	808	

On average, treatment household heads were about 47 years old, and had about 3 years of education; about 92% were married and 92% were male. Likewise, the control household heads were about 48 years old, and had about 2.6 years of education; about 92% were married and 94% were male. The treatment households had on average 5.8 household members and about 86,000 Birr worth of assets; 98% of them owned houses with an average of 2.4 rooms and spent about 288 Birr per month for lighting. Similarly, the control households had on average 5.8 household members and about 93,000 Birr worth of assets; 98% of them owned houses with an average of 2.4 rooms and spent about 270 Birr per month for lighting.

In a randomized control trial (RCT), it is important to evaluate whether control and treatment households have similar characteristics before the introduction of the intervention, referred to as a balancing test in the RCT literature. If a difference is observed, the variable which is the source of the difference needs to be controlled in the regression used to analyze the causal effect of the intervention.

We conducted a balancing test using both simple mean difference and regression analysis. Table 1 shows the mean difference between control and treatment units on key socio-economic characteristics, and Table 2 presents regression results of the balancing test. In both Tables 1 and 2, the treatment and control households are similar for most of the variables at the baseline, except the variables gender, age and education of the household head. In particular, control household heads were slightly older and slightly less educated, although the assignment of respondents to the two groups was random (Table 1). The regression for the balance test also shows that there were fewer male-headed households in the information treatment group (which was weakly significant). This implies we need to include these variables in our regression to analyze adoption and WTP.

Table 2. Balance Test Results (OLS regression]

	Information	
Variables	Coef.	se
Gender of household head (1=Male, 0=Female)	-0.204*	0.108
Marital status (1 if married, 0 otherwise)	0.140	0.096
Education of household head in years	0.010	0.006
Age of household head in years	-0.002	0.002
Household size	-0.003	0.010
Value of total assets in Birr	-0.000	0.000
Number of rooms in the house	0.013	0.025
Household connected to grid (1 if yes, 0 otherwise)	0.192	0.128
Household uses solar light (1 if yes, 0 otherwise)	-0.021	0.057
Household uses kerosene for lighting (1 if yes, 0 otherwise)	0.033	0.040
Household uses fuel wood for lighting (1 if yes, 0 otherwise)	0.016	0.073
Access to credit (1 if access to more than 400 Birr)	0.028	0.046
Distance to market	0.001	0.003
Distance to nearest road	0.000	0.000
Distance to nearest town	-0.001	0.002
Village has access to grid (1 if yes, 0 otherwise)	-0.024	0.051

Constant	0.571***	0.129
Observations	806	
R-squared	0.021	

Note: *** p<0.01, ** p<0.05, * p<0.1

On the descriptive experiment results, Table 3 shows the numbers and percent of households who adopted solar lanterns in the treatment and control groups. About 59% and 57% of treatment and control households, respectively, adopted the solar lantern. A simple mean difference test shows that there is no significant difference in the number of adopters between the two groups, which means that the information we provided did not make a significant difference in promoting the adoption of the solar lantern. The mean WTP of treatment households is slightly higher than control households but this difference is only weakly significant. Nonetheless, this weakly significant difference did not result in a significant difference in the number of adopters between the two groups. Figure 3 also shows maximum willingness to pay (WTP) of subjects for each of the treatment and control groups, where differences are observed only for some of the much larger extreme values for the treatment group compared with those for the control group.

Table 3. Number and Percent of Adopters in the Information Treatment and Control Groups

Variables	Treatment	Control	Mean difference	SE of the mean difference
Adopters (number)	239	229		
Adopters (percent)	59%	57%	0.022	0.035
Total	405	403		

Table 4. Mean WTP of Information Treatment and Control Groups

Variable	Treatment	Control	Mean Diff	SE
Mean WTP	154.7	140.2	14.5*	8.6

Note: *** p<0.01, ** p<0.05, * p<0.1

Figure 3. Maximum WTP of Households that Received Information vs those that did not Receive Information

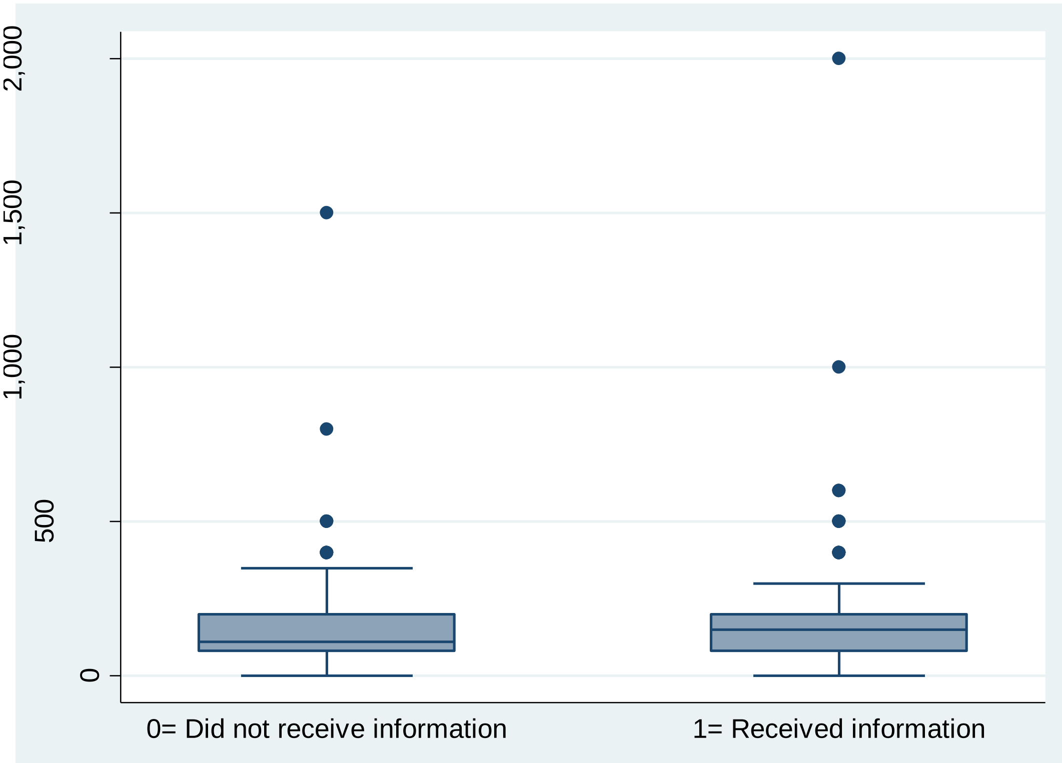
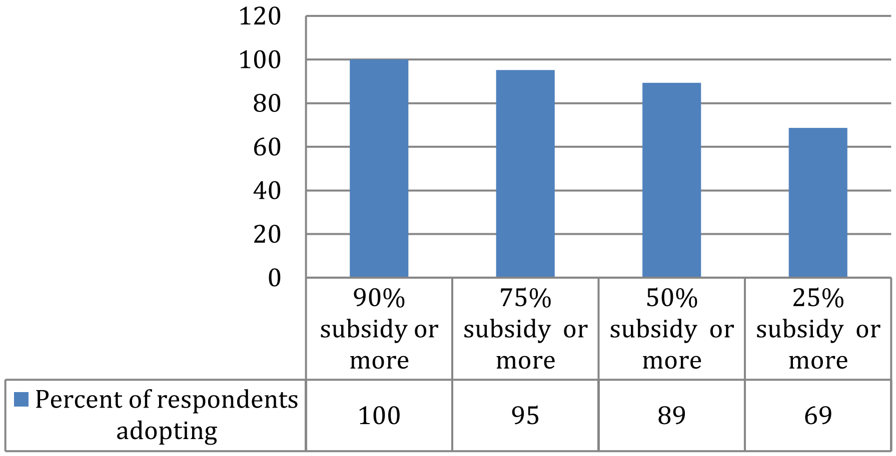


Figure 4 shows the percentage of actual adopters at different levels of subsidy. The percentages are computed from sites that received the corresponding prices or subsidies. We note from Figure 4 that the percentage of adopters increases when the subsidy increases. Specifically, for sites where the price drawn was with 90 percent subsidy or more, 100% of the respondents in those sites adopted the solar lantern. With a subsidy of 75 percent or more, the percentage of respondents adopting drops by only 5 percent (to 95 percent). The percentage adopting decreases to 69 percent in sites where the subsidy is 25 percent or more.[5] Although our sample is from low-income rural households, considering that the solar lantern under study is not very expensive (with a full price of less than 9 USD), with most of them sold through this study at much less than the full price, this suggests that most of the households in the study area would purchase the solar lantern at less than the full price. This could be partly because of previous negative experiences or diffusion of information about bad quality of solar lanterns in the market. Large quantities of solar lanterns are dumped into the market through illegal

[5] As noted, this is an advantage of our experimental design; unlike most previous studies, the fieldworkers actually did the random draw of the prices from the full list of 24 uniformly distributed prices in each of the 45 villages covered by the study. Because we use over 20 different subsidy levels, our approach provides flexibility, for example, in terms of being able to pick a wide range of subsidy levels and examining their implications; our approach also involves transparency, as the prices are drawn at random in front of the subjects.

channels, which is likely to affect the sustainability of the market.[6] This could also be because the subjects found the solar lantern to be too expensive.

Figure 4. Percent of Respondents Adopting by Subsidy Level



*The percentage of respondents adopting is calculated for sites where the subsidies actually applied based on the price drawn.

As discussed in the experimental design section, households were also given the opportunity to pay later (after a month). As a result, about 34% of the households who were willing to buy at the randomly drawn prices made the payment after a month, while 66% made the payment and received the solar lantern at the time of the experiment. Respondents who chose to pay later could have different reasons, including the fact that they were not ready to pay; in the context of the study area, the only way they could pay immediately was in cash. Not having the required cash at the moment and not being able to borrow from people they know from the sample households could be some of the major reasons for not paying immediately. However, it is possible that respondents who chose to pay a month later did so at least partly to benefit from the time delay due to the time value of money. This would in turn imply that the willingness to pay of these respondents would have been smaller if they paid immediately due to discounting. Considering that the difference in the date of payment is only one month and that the full price is less than 9 US dollars, with most of the respondents paying subsidized prices, the difference in the amount paid between those who paid immediately and those who

[6] Please see the following website about the diffusion of bad quality solar lanterns in Ethiopia: https://www.greentechmedia.com/articles/read/unlocking-an-energy-revolution-in-ethiopia-with-lessons-from-the-black-mark#gs.22joj9

paid after about a month may not be very large. As noted above, lack of cash at hand is also likely to be an important reason for not paying immediately. We may also note that those who paid immediately would be compensated by the benefit from use of the solar lantern immediately (a benefit which is not available to those who pay later and receive the solar lantern later) and therefore the differences between the two groups in terms of the net benefit obtained from the solar lantern may either disappear or may be very small. In the empirical analysis, we examine whether the results differ depending on whether the WTP of those who paid a month later is discounted at 1% to calculate the present value.[7]

Households whose WTP was less than the randomly drawn price were not given the opportunity to buy the technology even if they changed their mind for some reason, including a very low price drawn which is only slightly higher than their WTP. Of 340 respondents who did not adopt the solar lantern, 22 (which is less than 3 percent of the total sample) changed their mind and decided not to buy the solar lantern although their WTP was equal to or greater than the price drawn (referred to as decliners). We may also note that households were provided a show-up fee of 50 Birr. Because of this, one may expect that these households might have changed their mind if their WTP was less than the randomly drawn price of 50 Birr or less. In 11 out of the 45 villages (about 24% of the villages under study), the randomly drawn price was 50 Birr or less. Only 1 of the 22 respondents who changed their mind (less than 5%) was from a village where the randomly drawn price was 50 Birr or less.[8] However, those who changed their mind were not allowed to buy the solar lantern.

The randomly picked price ranged from 20 Birr to 250 Birr with a mean of 122 Birr. For about 50% of the respondents, the randomly picked price was 130 Birr or less (which is about half of the market price of the solar lantern). On the other hand, the maximum willingness to pay of the respondents was on average 147 Birr and ranged from 0 to 2000 Birr.[9] About 50% of the respondents were willing to pay more than 50% of the market price of the solar lantern. About 15% of the subjects were willing to pay more than the full price of the solar lantern. However, about two-thirds of those who were willing to pay more than the full price were willing to pay only 5 Birr more than the full price. Figure 5 depicts the demand curve for the solar lantern, showing willingness to pay and the corresponding percentage of

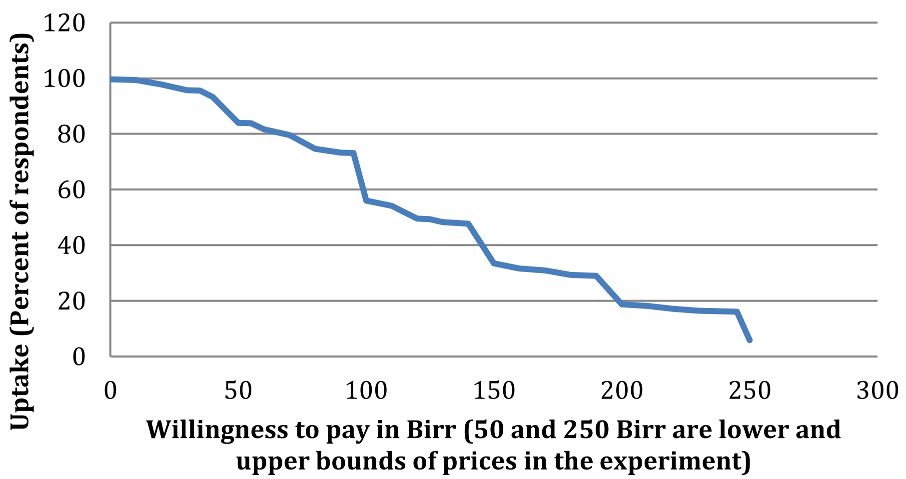
[7] Considering the arguments presented, we assumed that the discount rate for a period of a month is 1 percent, implying a simple discount rate of 12 percent per year.

[8] We may also note that less than 2% of respondents of villages where the randomly picked price was 50 Birr or less did not buy the solar lantern, suggesting that the take-up was high in villages where the randomly picked price was low combined with the show-up fee of 50 Birr that was given to each respondent.

[9] Considering that there were high extreme values (some of which were about 8 times more than the market price of the solar lantern under study), in the econometric analysis we tried to examine whether removal of such extreme values changes the results.

respondents after excluding decliners. We note from the figure that, unlike the findings of Grimm et al. (2020), we do not observe anchoring at the lower bound of the price range announced to the respondents (20 Birr). A possible reason is that we considered a wide range of prices relative to the market price—a range covering almost all possible prices, with the lowest price being only about 8 percent of the market price. We also see that willingness to pay appears to cumulate around multiples of 50, starting from 50 and ending with 250.

Figure 5. Demand for Solar Lantern



*WTP in this figure does not include decliners (who are less than 3% of the total sample). The uptake as shown by the percentage of respondents assumes that all subjects would purchase the solar lantern if their WTP is greater than the corresponding price drawn.

One of the key conclusions of the descriptive analysis is that, similar to the findings of Grimm et al. (2020) for Rwanda, most of the subjects would purchase the solar lantern only if it is subsidized. Thus, meeting the UN's SDG and the SEforAll objective of universal electricity access would be possible if some form of subsidy is introduced, at least for some of the population. As Grimm et al. (2020) note, providing solar lanterns on credit may not address the problem either.

5. Econometric Results

As discussed in the empirical strategy section, we estimate the effect of information and prices on households' adoption and WTP for the solar lantern.

5.1. Analysis of Adoption

Tables 5 and 6 present regression results showing the effect of information and prices/subsidy on the adoption of the solar lantern at continuous and dummy prices, respectively. Regression results are presented with and without controls.

Table 5. OLS Regression of the Effect of Information and a continuous Price on Adoption of Solar Lantern

	Without control		With controls	
Variables	Coef.	se	Coef.	se
Randomly drawn price	-0.004***	0.000	-0.004***	0.000
Information treatment	-0.005	0.037	-0.008	0.039
Information treatment X Randomly drawn price	0.000	0.000	0.000	0.000
Gender of household head (1=Male, 0=Female)			0.112	0.095
Marital status (1 if married, 0 otherwise)			-0.111	0.087
Education of the household head in years			0.005	0.005
Age of household head in years			-0.001	0.001
Household size			-0.003	0.007
Value of total assets in Birr			0.000	0.000
Number of rooms in the house			0.013	0.019
Household connected to grid (1 if yes, 0 otherwise)			-0.246***	0.068
Household uses solar light (1 if yes, 0 otherwise)			0.016	0.041
Household uses kerosene for lighting (1 if yes, 0 otherwise)			0.076**	0.033
Household uses fuel wood for lighting (1 if yes, 0 otherwise)			0.063	0.063
Access to credit (1 if access to 400 Birr or more, 0 otherwise)			0.030	0.033
Distance to market			0.004*	0.002
Distance to nearest road			0.000	0.000
Distance to nearest town			-0.000	0.001
Village has access to grid (1 if yes, 0 otherwise)			0.072*	0.039
Constant	1.109***	0.026	1.010***	0.100
Observations	808		806	
R-squared	0.399		0.423	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; Adoption =1 if household purchased at randomly drawn price and =0 otherwise

As shown in Table 5, the price variable has a negative sign and is statistically significant at the 1% level, suggesting that lower solar lantern prices can incentivize rural households to adopt the solar lantern. A one percent decrease in the price of the solar lantern increases the rate of adoption by 0.4%.

We define three dummy prices in Table 6 as less than 25% subsidy, 25% to 50% subsidy and 50% subsidy to 75% subsidy, while subsidy of 75% or more is the reference category. Regression results are presented with and without controls. As shown in Table 5, the price variable has a negative sign and is statistically significant at the 1% level, suggesting that lower solar lantern prices can incentivize rural households to adopt the solar lantern. A one percent decrease in the price of the solar lantern increases the rate of adoption by 0.4%. This is consistent with the descriptive results, which show that at full price (zero subsidy) there were only 5 households that adopted the solar device and that, when the subsidy changes to 25% of the price or less, only 38 households adopted the solar lantern. The number of adopters reached 53% only when the subsidy reached 90% of the price or less. Table 6 shows the effect of the different subsidy levels. The coefficients are interpreted relative to more than 75% subsidy, which is the reference category. The coefficients of the three subsidy variables are negative and statistically significant at the 1% level, showing that adoption is lower when subsidy decreases or price increases. The magnitude of the coefficients shows that the effect is stronger at higher prices or lower subsidy levels.

Table 6. OLS Regression of the Effect of Information and Dummy Prices on Adoption of Solar Lantern

	Without control		With control	
Variables	Coef.	Se.	Coef.	Se.
Less than 25% subsidy	-0.772***	0.045	-0.786***	0.049
25% to 50% subsidy	-0.656***	0.045	-0.649***	0.047
50% to 75% subsidy	-0.312***	0.067	-0.313***	0.071
Information	-0.041	0.025	-0.038	0.028
Information X Less than 25% subsidy	0.059	0.066	0.067	0.067
Information X 25% to 50% subsidy	0.082	0.067	0.063	0.069
Information X 50% to 75% subsidy	0.196**	0.088	0.176**	0.087
Gender of household head (1=Male, 0=Female)			0.116	0.092
Marital status (1 if married, 0 otherwise)			-0.105	0.086
Education of household head in years			0.002	0.005
Age of household head in years			-0.001	0.001
Household Size			0.000	0.007
Value of total assets in Birr			0.000	0.000
Number of rooms in the house			0.013	0.018
Household connected to grid (1 if yes, 0 otherwise)			-0.221***	0.070
Household uses solar light (1 if yes, 0 otherwise)			-0.034	0.042

Household uses kerosene for lighting (1 if yes, 0 otherwise)			0.078**	0.032
Household uses fuel wood for lighting (1 if yes, 0 otherwise)			0.070	0.064
Access to credit (1 if access to 400 Birr or more, 0 otherwise)			0.020	0.032
Distance to the market			0.003	0.002
Distance to the nearest road			0.000	0.000
Distance to the nearest town			0.000	0.001
Village has access to grid (1 if yes, 0 otherwise)			0.067	0.041
Constant	0.972***	0.014	0.839***	0.096
Observations	808		806	
R-squared	0.416		0.436	

Note: *** p<0.01, ** p<0.05, * p<0.1; Adoption =1 if household purchased at the randomly drawn price and =0 otherwise

Consistent with the descriptive results above, provision of information about the private and public benefits of the solar lantern did not make a significant difference in the rate of adoption (Tables 5 and 6). Further, a combination of price incentives and information (i.e., their interaction) also did not have a significant effect on adoption, except in the case where a higher subsidy level of 50% to 75% is interacted with information, which was significant at the 5% level. This suggests that a high level of subsidy along with information could increase adoption. Without a significant subsidy, providing information about the private and environmental benefits of this technology cannot provide enough incentives to significantly change behavior. These results are robust to inclusion or exclusion of control variables (Table 6).

In Tables 5 and 6, we also considered the effect of control variables on adoption. The results show that households that are connected to grid electricity are less likely to adopt the solar lantern, suggesting that the former is a preferred substitute for lighting. In contrast, households that used kerosene for lighting were more likely to adopt the solar lantern, suggesting that solar is a preferred substitute. Moreover, households that lived farther away from the market were more likely to adopt the solar lantern, suggesting that better access to solar lanterns increases adoption; but this is weakly significant. We also find that villages that are connected to the grid are more likely to have a higher adoption rate, which was not expected, but the coefficient is weakly significant.

5.2 Analysis of WTP

Table 7 presents the effect of information provision on individuals' WTP for the solar lantern. We find that information treatment does not have a significant effect on WTP. Similarly to the results for adoption, households that are connected to the grid have a lower willingness to pay compared with those not connected, which is expected. Moreover, households that have better access to credit have a higher willingness to pay for the solar lantern, suggesting that credit relaxes the liquidity constraint households face. Households that used fuel wood for lighting and are farther away from the market have a higher willingness to pay but these results are weakly significant.

Table 7. Effect of Information on WTP for Solar Lantern with Controls

Variables	Coef	Se
Information	14.391	8.962
Gender of household head (1=Male, 0=Female)	31.321	30.748
Marital status (1 if married, 0 otherwise)	-17.784	30.317
Education of household head in years	-0.259	1.331
Age of the household head in years	-0.262	0.317
Household size	-1.347	2.435
Value of total assets in Birr	0.000	0.000
Number of rooms in the house	2.667	5.462
Household connected to grid (1 if yes, 0 otherwise)	-55.462***	14.882
Household uses solar light (1 if yes, 0 otherwise)	-3.121	11.250
Household uses kerosene for lighting (1 if yes, 0 otherwise)	12.906	10.755
Household uses fuel wood for lighting (1 if yes, 0 otherwise)	30.371*	15.979
Access to credit (1 if access to 400 Birr or more, 0 otherwise)	16.523**	7.992
Distance to the market	1.524*	0.909
Distance to the nearest road	0.032	0.041
Distance to the nearest town	0.052	0.286
Village has access to grid (1 if yes, 0 otherwise)	5.231	9.287
Constant	94.889***	33.550
Observations	806	
R-squared	0.042	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

We also briefly discuss below the sensitivity of the analysis of WTP to the following three issues, in order: effect of extremely large WTP; effects of difference in WTP between those who collected the solar lantern after paying immediately and those who paid and also collected the solar lantern a month later; and the effect of removing respondents who did not purchase the solar lantern although they were winners (decliners).

We noted that there are some extremely large WTP values, with some of these being much higher than the maximum price of the solar lantern. Since we informed participants about the price range (the minimum and the maximum), considering the nature of the bidding mechanism we used, one may expect that for the respondent to be able to ensure buying the solar lantern, it would just be enough if WTP is the same as the highest price in the range and not more. Some subjects' WTP was quite high; in the most extreme case, it was 8 times the market price of the solar lantern. While such values may be a reflection of the true WTP of the subjects, some of these values may be considered too high. To examine possible effects of extremely large WTP, we run a regression after excluding these values. The main results are robust to removal of extremely large WTP (Appendix 1).

To examine the possible effects of difference in WTP of those who paid and collected the solar lantern a month later compared with those who immediately paid and collected the solar lantern, we discounted the WTP of respondents who paid about a month later at the rate of 1 percent per month. In this case, as well, the results of the regression analysis are robust to discounting of WTP (Appendix 2).

The results of the regression analysis of WTP are also robust to exclusion of respondents who declined to purchase the solar lantern in spite of stating willingness to pay an amount larger than or equal to the randomly drawn price (Appendix 3).

We also combined the three cases discussed above and the results (not reported here) are also robust to these changes.

6. Summary and Conclusion

About 620 million people in sub-Saharan Africa do not have access to electricity services. Off- grid electricity sources such as solar lantern are options available, especially to reach the rural poor living in remote and dispersed settlements, which increases the cost of grid-electricity significantly. However, penetration of off-grid electricity is also very limited. In Ethiopia, only 11% of rural households use off-grid electricity sources. The overwhelming majority of rural households continue to rely on biomass and kerosene as fuel sources for lighting. Thus, the Ethiopian government needs to devise effective policy instruments to achieve the goal of 100% electrification, where 35% of this plan is to be achieved via off-grid solutions such as solar technologies.

This study examined the role of information and subsidies as policy instruments in the adoption of and willingness to pay for solar lanterns. We use the BDM method to assess and analyze preferences of rural households towards solar lanterns. Our sample included 810 subjects from 45 sites. The experimental design involved dividing households in a site into two randomly selected groups, with one receiving information while the other did not.

Our results indicate that an increase in subsidy level (or a decrease in price) increases the rate of adoption. Provision of information about the private and public benefits of the solar lantern generally did not make a significant difference in the rate of adoption, except in cases where a high level of subsidy is combined with information provision.

Similar to the findings of Grimm et al. (2020), most of the subjects would purchase the solar lantern only if it is subsidized. Thus, meeting the UN SDG and the related SEforAll goal of universal electricity access would be possible if some form of subsidy is introduced, at least for some of the population. As Grimm et al. (2020) note, providing solar lanterns on credit may not address the problem either.

Our results also show that households who use kerosene for lighting are more likely to adopt the solar lantern. On the other hand, households that are connected to the grid are less likely to adopt and have a lower WTP for the solar lantern, suggesting that subjects prefer grid electricity to the solar lantern. Relaxing the liquidity constraint for households by providing them credit is also important, as households with access to credit have a higher WTP. Our results are robust to exclusion of extremely large WTP, exclusion of subjects who declined to purchase the solar lantern even if their WTP was higher than the randomly picked price, and consideration of differences in the time payment is made and the solar lantern is collected by subjects.

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Appendix

Appendix 1. Effect of Information on WTP for Solar Lantern with Controls (excluding extreme values)

Variables	Coef	Se
Information	9.489	5.765
Gender of household head (1=Male, 0=Female)	1.566	20.409
Marital status (1 if married, 0 otherwise)	0.824	17.303
Education of household head in years	1.576	1.003
Age of the household head in years	-0.274	0.241
Household size	0.254	1.573
Value of total assets in Birr	0.000	0.000
Number of rooms in the house	2.569	3.765
Household connected to grid (1 if yes, 0 otherwise)	-56.504***	14.270
Household uses solar light (1 if yes, 0 otherwise)	3.095	10.672
Household uses kerosene for lighting (1 if yes, 0 otherwise)	7.609	6.669
Household uses fuel wood for lighting (1 if yes, 0 otherwise)	24.177*	13.318
Access to credit (1 if access to 400 Birr or more, 0 otherwise)	12.234*	6.741
Distance to the market	0.788	0.521
Distance to the nearest road	0.012	0.030
Distance to the nearest town	0.318	0.244
Village has access to grid (1 if yes, 0 otherwise)	7.367	8.675
Constant	101.011***	20.979
Observations	800	
R-squared	0.06	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 2. Effect of Information on WTP for Solar Lantern with Controls (with late payments discounted)

Variables	Coef	Se
Information	14.479	8.903
Gender of household head (1=Male, 0=Female)	31.295	30.671
Marital status (1 if married, 0 otherwise)	-17.737	30.276
Education of household head in years	-0.263	1.325
Age of the household head in years	-0.263	0.315
Household size	-1.328	2.415
Value of total assets in Birr	0.000	0.000
Number of rooms in the house	2.659	5.424
Household connected to grid (1 if yes, 0 otherwise)	-55.364***	14.830
Household uses solar light (1 if yes, 0 otherwise)	-3.318	11.200
Household uses kerosene for lighting (1 if yes, 0 otherwise)	12.710	10.690
Household uses fuel wood for lighting (1 if yes, 0 otherwise)	30.342*	15.889
Access to credit (1 if access to 400 Birr or more, 0 otherwise)	16.417**	7.957
Distance to the market	1.518*	0.902
Distance to the nearest road	0.031	0.040
Distance to the nearest town	0.048	0.284
Village has access to grid (1 if yes, 0 otherwise)	5.168	9.237
Constant	94.837***	33.320
Observations	806	
R-squared	0.042	

Note: *** p<0.01, ** p<0.05, * p<0.1

Appendix 3. Effect of Information on WTP for Solar Lantern with Controls (with decliners excluded)

Variables	Coef	Se
Information	14.137	9.184
Gender of household head (1=Male, 0=Female)	30.219	30.660
Marital status (1 if married, 0 otherwise)	-17.783	30.255
Education of household head in years	-0.239	1.367
Age of the household head in years	-0.281	0.322
Household size	-1.206	2.476
Value of total assets in Birr	0.000	0.000
Number of rooms in the house	2.808	5.592
Household connected to grid (1 if yes, 0 otherwise)	-57.504***	16.600
Household uses solar light (1 if yes, 0 otherwise)	-4.123	11.574
Household uses kerosene for lighting (1 if yes, 0 otherwise)	11.477	11.065
Household uses fuel wood for lighting (1 if yes, 0 otherwise)	29.106*	16.652
Access to credit (1 if access to 400 Birr or more, 0 otherwise)	17.337**	8.131
Distance to the market	1.470	0.914
Distance to the nearest road	0.031	0.041
Distance to the nearest town	0.032	0.292
Village has access to grid (1 if yes, 0 otherwise)	3.225	9.498
Constant	98.522***	33.975
Observations	784	
R-squared	0.041	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 4.

INSTRUCTIONS TO BE READ BY THE INTERVIEWER TO MEMBERS OF THE GROUP THAT RECEIVES THE INFORMATION TREATMENT

Interviewer: Record which version of the instrument is used (1. Including additional information on private and public benefits of solar lanterns; 2. Not including information on private and public benefits of solar lanterns).

Private benefits of adopting the solar lantern are: savings on fuel expenditure such as kerosene and diesel that you use for lighting (reduction in energy expenditure per lumen); three times brighter light covering larger area compared with kerosene or diesel lamps, which may especially help students who study in the evening; savings in time spent to purchase kerosene and diesel with repeated trips to towns and collecting fuelwood that you may use for lighting; reduction in the risk of suffering from pulmonary and heart diseases from indoor air pollution; and reduction in fire hazards associated with use of kerosene lamps and

Public benefits of adopting solar lanterns include outdoor air pollution reduction, forest conservation and availability of fuelwood for future generations due to reduced use of fuelwood for lighting, and reducing battery waste.