Decreasing Emissions by Increasing Energy Access? Evidence from a Randomized Field Experiment on Off-Grid Solar Lights *

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Abstract

Climate change and energy poverty in low- and middle-income countries are global challenges that are sometimes in tension with each other. This paper analyzes a randomized intervention that addresses both: distribution of solar lights to replace kerosene lamps. The solar lights strongly reduce carbon emissions from kerosene by half, while at the same time lowering household expenditures and improving health and subjective well-being. Providing lights for free, rather than charging a co-pay, boosts take-up without lowering usage. Access to solar lights can therefore be a highly cost-effective climate interventions, which at the same time increases the welfare of the poor.

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1 Introduction

The global community faces two critical challenges that may seem at odds with each other: climate change and a lack of access to modern energy for the world's poor. Over 750 million people still have no access to electricity in their homes, out of which 80% live in Africa (42% of the total population) (IEA, 2023). An often-raised concern is that access to energy for these populations would jeopardize the global goal of fighting climate change (United Nations, 2021). However, this trade-off may not exist in situations where those without access to electricity instead rely on energy biomass such as kerosene, which is particularly detrimental to global climate (IEA, 2011). Kerosene lamps, in particular, are estimated to emit around 270,000 tons of black carbon per year (Lam et al., 2012). In these situations, providing access to clean energy may at the same time reduce energy poverty and carbon emissions.

In recent years, production costs for solar energy have decreased dramatically, making off-grid solar a potential cost-effective solution to provide low-income households with cheap and clean energy. However, examples abound of "development solutions" with promising engineering projections from novel devices that ended up having much lower impacts in practice, for instance, due to low adoption or costly maintenance requirements (Davis et al., 2014; Bensch and Peters, 2015, 2019; Hanna et al., 2016). It is therefore key to understand to what extent access to new technologies such as solar lights indeed reduces carbon emissions (Beltramo et al., 2023). While prior RCTs have studied the effects of solar lights on education, health (through reduced indoor air pollution), kerosene consumption, and economic and subjective well-being, (Furukawa, 2012, 2014; Hassan and Lucchino, 2016; Aevarsdottir et al., 2017; Aklin et al., 2017; Furukawa, 2017; Grimm et al., 2017; Kudo et al., 2019a,b; Sharma et al., 2019; Mahajan et al., 2020; Stojanovski et al., 2021; Wallach et al., 2022), causal estimates on their impact on carbon emissions have so far been lacking.[1]

This study analyzes both the demand for and impacts of access to solar lights through a randomized field experiment in rural Kenya, where kerosene was the predominant energy source for lighting. The solar lights strongly reduce carbon emissions, while at the same time lowering expenditures of these very poor households and improving their health and subjective well-being. Over two years, access to a solar light that costs USD 9 leads to a

[1]While Wagner et al. (2021) analyze the environmental benefits of solar home systems in terms of CO_2-eq emissions, they rely on cross-sectional evidence on solar home systems ownership.

reduction of 9.13 kg of CO_2 and 1.63 kg of black carbon (BC). According to the central estimate from the climate science literature, this amounts to a reduction of $1,371$kg in CO_2-equivalents (CO_2-eq) in terms of climate impacts.[2] At current carbon prices of the EU carbon market, this reduction would amount to USD 120, and at the currently estimated social costs of carbon by the U.S. Environmental Protection Agency (EPA), this corresponds to a social value of USD 260. However, since carbon markets do not include BC emissions (so far), carbon credits cannot be used to pay for this type of intervention.

The school-based intervention we evaluate was conducted in 2015-2016 among about 1,400 households and consists of five treatment arms in which solar lights were offered to randomly selected households at different price points. This allows us to study both the price elasticity of demand and usage and the impacts of the lights on households and on the environment. To measure these outcomes we combine survey data from 7-8 months after the distribution of the lights, administrative educational records as well as—for a subset of the study sample—electronic sensor data on usage.

Before analyzing the impacts of the solar lights, we investigate the role of price, as well as information and transaction costs, for take-up and usage. The lights were provided at the school to the guardians of selected students. At the end of a baseline survey, guardians were either directly offered a free light, or given a voucher to redeem such a light at the market price of USD 9, or at subsidized prices of USD 7 or 4, respectively. Comparing take-up of the different voucher treatments shows that demand is highly elastic to price: for a 1% increase in price, take-up drops by 0.5 percentage points.

The fact that take-up is still 31% for participants who receive a voucher to purchase the light at market price suggests that information and transaction costs may present an important barrier to take-up.[3] Similarly to studies from other contexts of good distribution at different price points (e.g., Kremer and Miguel, 2007; Dupas, 2009; Ashraf et al., 2010; Cohen and Dupas, 2010; Kremer et al., 2011), we find that while take-up responds strongly to prices, usage of the lights conditional on take-up is not lower when lights are distributed

[2] CO_2-equivalents are a measure to compare the climate impact of different sources of emissions. Non-CO_2 emissions are converted to equivalent quantities of carbon dioxide with the same global warming potential. BC has a particularly strong impact on climate change (Bond et al., 2011). The climate science literature calculates a range of estimates for the conversation factor of BC to CO_2-eqs. Our preferred estimates are based on the central estimate in the climate literature, but we also report results for the full range of estimates.

[3] For instance, in our setting, locations where solar lights can be bought are often quite a distance away.

for free. Light usage is also similar for a different, larger and mobile-charging-enabled solar light, which was distributed for free in a fifth treatment arm. Data from the sensors shows that usage does not decline over time.

The solar lights are used for an average of around 3.3 hours a day. Having a solar light also helps households to have more consistent lighting, as there are fewer lighting interruptions.[4] Owning a functioning solar light almost fully replaces the use of one kerosene-fueled lamp.As a result, households purchase 16 fewer liters of kerosene on average, a 50% reduction. Taking into account which type of kerosene lamp any given household used prior to the intervention, we can estimate that this translates into a reduction of 71,296g of CO_2-eq emissions per month, a 50% drop compared to the control complier mean. Given the costs of the basic light at USD 9 and the larger light at USD 24, over two years this implies an abatement cost per ton of CO_2-eq emissions averted of USD 6.56 and USD 17.60, respectively, taking into account a monthly breakage of the lights of 1.15%. These costs are substantially below the current price of carbon in the EU of 80€ (Trading Economics, 2023) or of the EPA's recommended social cost of carbon estimate of USD 190 (U.S. Environmental Protection Agency, 2022).

Beyond the environmental benefits, access to the solar lights also generates private benefits to the household. First, monthly energy expenditures fall substantially. This is the only outcome for which we find significant differences between the basic and the larger light. The reason is that in addition to the reduction in kerosene consumption, the larger light also substantially reduces expenditures for mobile phone charging. As a result, total monthly energy expenditures fall by USD 1.3 for the basic and USD 2.4 for the larger light. For both types of light, the net present value (NPV)—i.e. the discounted stream of future reductions in energy expenditures minus the cost of the light—is positive. It amounts to USD 7.14 for the basic and USD 5.82 for the larger light, and the lights pay off in terms of private financial benefits after 9 and 19 months, respectively.

Finally, we also investigate the impacts of access to solar lights on health, education, and subjective well-being. Kerosene lights emit noxious fumes that lead to indoor air pollution, which is detrimental to respiratory and eye health.[5] Using standardized survey questions

[4] Lighting interruptions, in which households have to sit in the dark, usually occur when they run out of fuel for other types of lights, which most commonly is the result of financial constraints.

[5] In the longer-term, indoor air pollution can also lead to severe illness and death (WHO, 2016). However, our sample size and the duration after which we observe the impact do not allow us to measure such effects.

from the health literature we find significant improvements in both respiratory and eye-related symptoms for both students and guardians, ranging from 0.15 to 0.27 standard deviations.

Combining our survey data with administrative test scores we can analyze the impacts on both educational inputs and outcomes. We observe improvements of the former but not the latter. Students report spending more time doing homework after dark, being more likely to complete their homework, and increased school attendance. However, we see no effects on test scores nor on the probability of taking part in the national standardized graduation exam (KCPE). However, we cannot rule out that this absence of observable impacts is a result of within-school spillovers (both from sharing the light and from potential learning spillovers).

Finally, we measure impacts on a number of psychological outcomes. There is a positive effect on the average of all outcomes for both guardians (of about 0.07 standard deviations) and students (0.11 standard deviations). In particular, guardians' views improved significantly in terms of whether their economic situation had improved over the last three months, and whether their life as an adult would be better than their parents'.

Our study contributes to two main literatures. First, we add to the economics literature on access to electricity in low-and middle-income countries. Much of this literature has focused on the impacts and cost-effectiveness of providing people with access to the electric grid (e.g., Lee et al., 2016a,b, 2020; van de Walle et al., 2015).[6] However, in many areas of the world, access to the grid is likely still years or even decades away. In addition, even where access to the grid is available, it is often unreliable (e.g., Ayaburi et al., 2020). There has therefore been a debate on whether off-grid or on-grid solutions should be prioritized in the short- and medium-run (e.g., Ortega-Arriaga et al., 2021; Leo, 2015; Dagnachew et al., 2018). Off-grid alternatives may in particular be more affordable for households in poor, isolated regions (Lee et al., 2016b) where on-grid schemes may have low take-up rates or be challenging to implement (Lee et al., 2016a,b; Deichmann et al., 2011; Urpelainen, 2014). An alternative to grid-access are solar- (or hydro-) powered micro-grids. These can power multiple household appliances in addition to lighting. However, they are substantially more costly—and therefore usually not affordable to the poorest—and technologically more

[6]For a review of impact estimates, see Bonan et al. (2014) on access to electricity and Bos et al. (2018) on access to the electric grid in Africa.

challenging to install and maintain (Fowlie et al., 2019; Aklin et al., 2017; Millinger et al., 2012). This paper contributes to our knowledge of the benefits of off-grid solutions by focusing on one of the lowest-cost off-grid products, small solar lights.

Second, our paper contributes to the literature on the economics of climate change, and in particular to the long-standing debate on whether reducing global poverty is in tension with global efforts to slow down climate change, as lower poverty often implies higher carbon emissions (Ravallion et al., 2000; Rojas-Vallejos and Lastuka, 2020; Bruckner et al., 2022; Wollburg et al., 2023; Fouquet, 2016). This paper provides an example of an intervention that can overcome this trade-off, in the sense that it provides a clean technology that at the same time reduces household poverty and carbon emissions (World Bank, 2022; Dagnachew et al., 2018; Alstone et al., 2015; Fetter, 2022). As Wolfram et al. (2012) point out, reducing poverty by increasing access to energy can even provide win-win solutions. Our intervention provides such an example.

2 Background and Study Design

2.1 Context

Global Trends of Light Usage and Policy Environment

Increasing access to electricity is a key global goal (e.g. Sustainable Development Goal 7 (United Nations General Assembly, 2015)). While a lot of progress has been achieved in recent decades, in rural and remote areas expanding access to the electric grid tends to be very costly (Bos et al., 2018; Golumbeanu and Barnes, 2013). Thus, off-grid energy systems[7], of which solar lights are one example, have been increasingly used as a cost-effective alternative until the electric grid can reach everyone (Barnes, 2011; Rahman et al., 2013; Come Zebra et al., 2021). The International Renewable Energy Agency (IRENA) estimates that between 2012 and 2021, the number of people worldwide using basic solar lights grew from 16 to 138 million (IRENA, 2022).

Kerosene Emissions and their Impacts

Kerosene-fueled lamps produce three main types of emissions: carbon dioxide (CO_2), particulate matter 2.5 ($PM_{2.5}$), and black carbon (BC). $PM_{2.5}$ are inhalable fine particles with

[7]Off-grid energy is energy that is generated autonomously and independently of the public grid.

a diameter of 2.5 micrometers or less. These air pollutants are particularly detrimental to health. BC (colloquially also referred to as soot) is a component of $PM_{2.5}$ and is estimated to be the second most important agent contributing to global warming after CO_2 (Bond et al., 2013). At least 88% of the $PM_{2.5}$ mass that kerosene lamps emit is BC (Lam et al., 2012).

Different types of kerosene lights produce different amounts of emissions per kilogram of burnt kerosene.[8] The most common ones are tin lamps and kerosene lanterns (pictured in Figure 1). Lam et al. (2012) find emissions of 2,770g of CO_2, 93g of $PM_{2.5}$, and 90g of BC for tin lamps, and 3,080g of CO_2, 13g of $PM_{2.5}$, and 9g of BC for kerosene lanterns.[9]

Environmental Effects: BC acts both fast and locally. Though less often in the headlines, it has much stronger effects than CO_2 on the climate per kg emitted. While BC only remains in the atmosphere for a short period of time, its effects can continue for years and even decades, due to the thermal inertia in the climate system (Szopa et al., 2021). Climate scientists have estimated the impact of BC on climate change in terms of CO_2 equivalents (henceforth referred to as CO_2-eq). The climate impact of BC depends on its atmospheric abundance and concentration (Bond et al., 2013, 2011), and therefore varies across world regions. Bond et al. (2011) provide CO_2-eq estimates from BC emissions through fuel-burning activities by region. Their central estimate for Eastern Africa is 836 CO_2-eq per kg of BC emitted. We show results using this estimate, as well as a range of alternative conversion factors from BC to CO_2-eq from the climate science literature.[10]

Health Effects: Kerosene-fueled lighting also has adverse health effects through indoor air pollution, especially from $PM_{2.5}$. Indoor air pollution is considered one of the most important environmental health risk factors worldwide (WHO, 2016). While lights burn less kerosene than cookstoves, their impact on health may still be substantive, in particular,

[8] Conversion of liters to kilograms of kerosene depends on the density of the kerosene used. Kerosene sold in Kenya must have a density of between 0.771 and 0.830kg/dm^3 (TotalEnergies, 2022). We take the mid-point of this interval and calculate with 0.8 kilograms per liter.

[9] This study was conducted in Kenya's neighboring country Uganda, where the type of lights and fuel used are very similar to our context.

[10] The parameters chosen to calculate the conversion factors from BC to CO_2-eq are subject to a substantial degree of uncertainty. We therefore report results using a number of alternative conversion rates. First, we show results using the lower and upper bounds of the Bond et al. (2011) conversion factor. Second, we show estimates using an alternative approach from climate science, calculated in (Bond et al., 2013), which does not have different conversion factors by geographic region—as well as the lower and upper bound of this alternative approach. For all conversion factors, we use the version with a 100-year time horizon—as opposed to 20 years—since this is more conservative (i.e. provides lower conversion factors).

because people sometimes spend many hours sitting very close to the lights.

While indoor air pollution from kerosene burnt for cooking has been studied extensively (e.g. Berkouwer and Dean, 2022), the role of lighting is less clear.[11]

The Kenyan Context

Increasing access to electrification for Kenyan households has been a key priority of the government in recent years. As a result of the various initiatives of the government and of the Rural Electrification Authority, the rate of access to electricity (grid and off-grid combined) grew from 42% in 2015 to 76% in 2021 (World Bank, 2021a). Nevertheless, about 32% of the population in rural regions of Kenya still did not have access to electricity in 2021 (World Bank, 2021b). The continued weakness of Kenya's power transmission and distribution infrastructure has led to a high system cost, which limit electrification in the country (Osiolo et al., 2017). At the same time, individual barriers, such as distance to transformers, prices, income, and the frequent issues that plague the Kenyan electricity grid (black-outs, breakdowns, voltage drops, and long restoration times) lead to low take-up by households, even where electrification is theoretically possible (Moner-Girona et al., 2019). Therefore, renewable off-grid technologies, including solar energy sources, are considered by many to be an important part of the solution to address the Kenyan electrification gap (Moner-Girona et al., 2019; Zeyringer et al., 2015).

At the time of our intervention, in 2016, about 35% of Kenya's households relied mostly on kerosene for lighting (KIHBS, 2018).[12] Since our study took place in a rural part of Kenya, where few people had access to the electric grid, 93% of study participants used kerosene as the main source for lighting prior to the intervention. By lamp type, at baseline, 63% of households in our control and free treatment groups used only tin lamps during the preceding month, 36% used both tin lamps and kerosene lanterns, and 0.4% used only kerosene lanterns.

At the same time, solar lights were not always easily available. In our study, 47% of respondents in the control group mentioned at baseline that they had never seen a solar light being sold before. Of those who had seen a light being sold, only 9% had seen it in

[11] According to WHO (2021) "each year, 3.2 million people die prematurely from illness attributable to the household air pollution caused by the inefficient use of solid fuels and kerosene for cooking".

[12] Around 41% powered their light mainly through the electric grid, 14% used solar lights, and 9% alternative sources such as fire, wood and batteries.

their own village, while 69% saw it at the closest market center and 24% only in a larger city.

2.2 Intervention

We conducted a randomized field experiment between June 2015 and March 2016, which consisted of the distribution of solar lights in schools in rural Kenya to investigate the demand for solar lights and their potential environmental, financial, health, and educational benefits. The intervention took place in 20 primary schools (grades 5-7) in Western Kenya (sub-counties Nambale and Teso South) in partnership with SolarAid, a large distributor of portable solar lights in Kenya. (See Appendix B for an in-depth description of the sample selection, randomization, treatment assignment, light distribution, and surveys and Figure B.1 and B.2 for a graphical representation of the research design and timeline.)

Sampling Frame and Randomization: Out of 97 eligible rural public schools, we randomly selected 10 schools from each sub-county.[13] The sampling frame included the 3,360 households that had at least one child in grades 5–7.[14] Among these households, we randomly selected 1,410 students into treatment and control groups (stratified at the school level). The final study sample consists of $1,286$ households, since there was about 6.9% attrition in the endline survey (discussed in Section 3.6).

Baseline Survey and Treatments: The intervention started with a baseline survey with the students, followed by another survey of their guardians (usually a parent or other relative) at the school.[15] The baseline surveys were conducted between July and August 2015. The solar lights - or vouchers to purchase a solar light - were distributed to the guardian at the end of their survey.[16] There were five different treatment arms, which varied along two dimensions:

[13]Excluded from this sample were thirty schools that had less than 200 students, were boarding schools, unisex, special needs schools, part of other research projects, or too far away to be reached within a day from the field office.

[14]Students in grades 1–4 were not included since it would have been hard for them to answer survey questions and students in grade 8 would have left school before the study had ended. For households with more than one student in grades 5–7, we randomly selected one student to be in the sampling frame.

[15]At the end of the student survey, we gave students a note that invited their guardian to come to the school for the guardian survey. We also asked students for their guardian's name and phone number, so that if the guardian did not come to the school, surveyors could contact them and conduct the survey at home or at their workplace. (The share of guardians who did the survey at the school is balanced across treatment arms.) 50.6% of guardians were the mother, 28.9% the father, 7.8% the grandmother, 3.8% the aunt, 2.8% the grandfather, and 2.5% the uncle.

[16]To make participants aware that it was determined by chance whether they received a light, a voucher, or nothing, we designed a text message process that informed them about what they "won" in a way that was similar to text message-based lottery games that are common in Kenya.

price and type of light (see Figure 1 for a graphical representation of the treatment arms and pictures of the different types of lights). The former allows us to estimate the price elasticity of demand, the latter to compare the impacts of a basic light vs. a larger light. The different treatment arms are as follows:

1. Free basic light (N=200): This light provides up to 27 lumens (a measure of brightness) and has a battery life of 8.1 hours at maximum brightness. For comparison, a simple kerosene tin lamp provides around 8 lumens and a kerosene lantern around 45 lumens (Mills, 2003). The market price of this light was USD 9.

2. Voucher for basic light with high subsidy (N=209): Guardians received a voucher to purchase a basic solar light for USD 4 (i.e., with a subsidy of USD 5 compared to the market price of USD 9), which they could redeem at the school within 4–6 weeks. Surveyors also showed participants a light and provided basic information about its features. The voucher contained the respondent's name and was not transferable.

3. Voucher for basic light with low subsidy (N=201): This treatment was identical to that of group 2, except that the voucher was to purchase a basic light at the school for USD 7 (i.e., with a subsidy of USD 2).

4. Voucher for basic light at market price (N=200): This treatment was identical to that of groups 2 and 3, except that the voucher was to purchase a basic light at the school for USD 9 (i.e., without a subsidy).[17]

5. Free larger light (N=200): This treatment was identical to that of group 1, but the guardian received a free larger solar light. This light provides up to 98 lumens, has a battery life of 5.4 hours at maximum brightness and is enabled for mobile phone charging. The market price of this light was USD 24.

6. Control group (N=400): Households in this group were not offered any light or voucher.

Endline Survey: 7-8 months later, we conducted endline interviews with students and guardians. The student endline surveys were again conducted at the school, the guardian

[17] In addition to helping us estimate the price elasticity of demand, this treatment also helps estimate the effect of the reduction of information and transaction costs provided by the intervention, in comparison to the control group, which could of course purchase a light on their own, but often had to travel far for this and did not get any information about the light.

endline surveys took place at their home.[18]

2.3 Data

We combine data from baseline and endline surveys (with both the students and their guardians) with electronic sensor data from a sub-sample of the solar lights, and administrative data on students' test scores.

Baseline Surveys: The student baseline survey includes information about the students' school attendance, homework, ownership and usage of lighting sources (including solar lights), time use, and health symptoms. The guardian survey covers guardians' and households' baseline characteristics, such as household size, economic activities, connection to the electric grid, and ownership and usage of lighting sources, including solar lights.

Endline Surveys: The student survey includes questions on time use, lighting use (hours of light use, usage of lights during specific activities, specifically during homework, and ownership and usage of a solar light), eye and respiratory health, education, and psychological outcomes. The guardian endline survey also includes questions on time use, lighting (hours of light use, ownership of differential light types, particularly of a working solar light, usage of lights during specific activities), eye and respiratory health, and psychological outcomes and in addition contains questions about energy sources and household expenditures.

We undertook multiple measures to increase the share of participants who could still be located for the endline survey.[19] As a result, we were able to locate 93% of guardians in the endline survey. The guardian endline survey is crucial to measure the impacts of having a working solar light, as it includes the question of whether the household owns a working solar light at endline (our first stage outcome variable for the LATE effects). Correspondingly, our main sample includes the $1,286$ households where the guardian could be reached for the endline survey.

Guardian attrition in the control group is 8.3%, but it is somewhat lower among treated households (see Section 3.6). We therefore provide robustness checks accounting for differen-

[18]If the student was absent during the survey day, surveyors attempted to survey them at a later date either at the school or at home. Similarly, if the guardians were not home the first time, the surveyor attempted to interview them another day.

[19]For instance, asking guardians in the baseline survey for own and alternative phone numbers and directions to their home, tracking students who were not present at school on the day of the endline survey, conducting guardian follow-up interviews at home and booking their appointments via phone or locating them through village elders.

tial attrition (Lee-bounds (Lee, 2009) and Inverse Probability Weighting (Wooldridge, 2002, 2007)). Results are highly robust to adjusting for attrition. Among households with no guardian attrition, 8.4% of students could not be reached for the endline survey. Therefore, estimates for outcomes reported by students have a smaller sample size of $1,203$. For student attrition, the difference between treatment and control groups is not statistically significant. For completeness, we nevertheless provide robustness checks for this attrition as well.

Sensor Data: Approximately 33% of the solar lights had a sensor installed that recorded at what times the light was on. This data was collected through home visits 1, 3, and 7 months after distribution. Unfortunately, matching the sensor data with survey responses was only possible for approximately two-thirds of the sensors.[20] We therefore only use these data to illustrate general patterns of light usage over time.[21]

Administrative Test Data: We collected test scores from end-of-term exams in the schools for all tested subjects (English, math, science, social studies, and Swahili). For students who were in grade 7 at the start of our intervention, we also obtained results from the Kenyan standardized primary school graduation exam "Kenya Certificate of Primary Education" (KCPE) which students take in the 8$^{\text{th}}$ grade.

Piloting and Qualitative Data Collection: Prior to the intervention, we also conducted semi-structured interviews and focus groups to gain more information about the context and to strengthen the study design and survey instruments. This qualitative data collection included teachers (in other schools in which our partner SolarAid had distributed lights before), as well as field staff and executives from SolarAid, and five focus groups with users and non-users of solar lights. We also piloted both the intervention and the survey instruments before the start of the study.

Balance Tests and Summary Statistics

Table 1 shows the balance of randomization and summary statistics at baseline. Column (1) displays the means and standard deviations for the control group. For each row, Columns (2) to (6) show coefficients and standard errors from regressing the baseline variable on treatment dummies for each treatment arm, and Column (7) shows results from a similar regression

[20] The reason for this is that in the process of fieldwork management, the dictionary file that linked the sensor IDs with the household IDs was compromised.

[21] More details on the installation and functioning of the sensors are discussed in Rom et al. (2020) and information on the processing of the sensor data can be found in the Data Appendix.

comparing all treatments combined to the control group. All regressions include school-fixed effects since the randomization was stratified at the school level. The F-test analyzes the joint significance of all baseline outcomes compared to the control group and is estimated using stacked regressions following Lee and Lemieux (2010) and Pei et al. (2019). While the F-tests show no systematic imbalances, 8 out of 90 individual coefficients are statistically significantly different from zero (as can be expected due to random chance). Since 6 of these coefficients refer to the gender of either the student or the guardian, we include gender-fixed effects in all of the following specifications.[22]

As Table 1 shows, only 1.3% of households have a connection to the electric grid and the share that already owns a solar light at baseline is 5.3%. Households include close to seven people on average and over 99% of them conduct agricultural activities. 37% of students are in grade 5, 36% in grade 6 and 27% in grade 7, and students are on average 13 years old. Around 57% of students and 64% of guardians are female. In 78% of cases the guardian is the student's parent, for 11% it is a grandparent. We also check whether differences in baseline survey modalities are balanced across treatment arms, i.e., whether the guardian did the interview at the school (vs. at home) and whether the student was in the original sample or is from the replacement list.[23]

2.4 Empirical Strategy

Our empirical strategy proceeds in four steps. First, we analyze take-up and endline ownership by treatment arm. Then, we compare light usage across treatment arms conditional on take-up. Third, we estimate the local average treatment effects (LATE) of owning a working solar light on various environmental and household outcomes. We benchmark our LATE using the "control complier mean" (CCM). We also discuss Intent-To-Treat estimates and spillovers.

Take-Up and Endline Ownership

To understand the impact of the treatments on solar light ownership, we separately show take-up—the share of participants who received a solar light through the program—and endline ownership—the share who owned a working solar light at the time of the endline

[22] Results are similar without gender-fixed effects as we show in Section 3.6.

[23] If a student was not present for the interview, a replacement was selected following a predetermined randomized backup list.

survey—by treatment arm. These two measures can differ because some households already owned solar lights prior to the intervention, some purchased other solar lights on the market during the study period, and some lights broke before the endline survey or might have been given away.

Usage

Conditional on owning a solar light, its usage could potentially differ across treatment groups because of selection effects (e.g., households that purchase the light at a higher price may be different) or treatment effects (e.g., households might use the light differently as a result of having paid for it), or because usage might be different for the larger light compared to the basic light. Whether this is the case will inform our empirical strategy.

To address this, we estimate the LATE on solar light usage separately for each treatment arm using two-stage least-squares (TSLS) regressions. In the first stage, we use treatment assignment as an instrument for the probability of owning a working solar light. This gives us five first-stage regressions that include households in the control group and in each respective treatment arm.

In the second stage, we estimate the impact of each treatment arm on solar light usage in the full sample, with a separate instrument for each treatment arm. We simultaneously estimate these regressions using a stacked regression in order to test for heterogeneity in usage across treatment arms. We include gender and school fixed effects and cluster standard errors at both the school and the household levels to account for the fact that households are included repeatedly when stacking regressions.

Conditional on owning a working solar light, usage does not vary across treatment arms. Hence, for most of our impact analyses, we estimate pooled effects of owning any functioning solar light across all treatment arms as described below.[24]

Impacts of Solar Lights

To analyze the effect of owning a functioning solar light on our outcomes of interest such as carbon emissions, household expenditures, health, education, psychological well-being, and safety, we estimate the LATE. Since take-up varies by treatment, but usage conditional on

[24]When results do differ by type of light, we report them separately for the larger and basic light. This is the case for energy expenditures, for which even though hours of usage are the same, impacts differ by type of light. We also report results separately by treatment arm for all other main outcomes in the Appendix.

owning a light does not, we include each treatment as a separate instrument in the first stage, and pool across all treatments in the second stage. This gives us an estimate of the pooled LATE of having a working solar light. Specifically, we estimate the following equations using TSLS. In the first stage, we estimate:

$$solar\_works_i = \pi_1 T_{i1} + \pi_2 T_{i2} + \pi_3 T_{i3} + \pi_4 T_{i4} + \pi_5 T_{i5} + \zeta_i + \gamma_j + u_{ij} \tag{1}$$

Where $solar\_works_i$ is a binary indicator of whether the household i owns a working solar light at endline, T_{ik} are binary indicators for treatment assignments of household i to arm k, ζ_i represents gender fixed effects, γ_j school fixed effects, and u_i is the error term, clustered at the school level.[25] The sample for each first-stage regression consists of households in the control group and the respective treatment arm k. In the second stage, we estimate:

$$y_{ij} = \beta \widehat{solar\_works}_i + \xi_i + \mu_j + e_{ij} \tag{2}$$

Where y_{ij} represents the outcome of interest, ξ_i gender fixed effects, μ_j school fixed effects, and e_i is the error term, clustered at the school level. Under standard IV assumptions, β represents the LATE of owning a working solar light on the outcome of interest for compliers in the pooled treatment group, i.e., on households that own a working solar light at the time of the endline survey as a result of the pooled treatment.[26]

Comparison Mean

To benchmark the magnitude of our estimates, we calculate the "control complier mean" (CCM), following (Katz et al., 2001). The CCM is the average outcome of those households in the control group that would have taken up the treatment had it been offered to them. It is calculated as the mean outcome among compliers in the treated group minus the LATE estimate. Since some participants in the control group also owned a solar light, we estimate the CCM using the correction proposed by Heller et al. (2013).

Intent to Treat

The Intent-To-Treat estimates can be directly derived from the LATE estimates by dividing the LATE estimates by the share of compliers. In our study, 17.4% of participants are

[25] We include school fixed effects in all estimations due to the fact that randomization was stratified at the school level and not all schools have the same share of participants across treatment arms.

[26] For robustness, we also show the main results without gender fixed effects in the Appendix.

always-takers (i.e., participants in the control group who owned a solar light at the time of the endline survey). In the treatment arms, there are 9.3%, 19.3%, 31.5%, 61.2%, and 60.1% of never-takers in the free mobile light, free basic light, high subsidy voucher, low subsidy voucher, and market price voucher treatment, respectively (i.e., participants who did not acquire a solar light or whose solar light had broken by the time of the endline survey). Accordingly, the ITT estimates are around 26.8%, 36.7%, 48.9%, 78.6%, and 77.5% smaller than the LATE estimates for the free mobile light, free basic light, high subsidy voucher, low subsidy voucher, and market price voucher treatment, respectively.

Spillovers

Given that randomization took place within schools, we cannot rule out that there might be spillovers between treatment and control households. This could lead to a downward bias in our estimates, making them a lower bound of the true effect. In particular, there could be spillover effects from sharing the light.[27] We collected the following descriptive evidence on light sharing. Only 1.6% of guardians and 1.2% of students who received a solar light through the study program shared it with someone else from the same school, and only 21 children ever took the light to school.

At the same time, 28% of students in the control group report going to someone else's house to do homework and personal studies in the week prior to the survey. Among these students, over 46% mention that they do this to have access to a better lighting source. In line with this finding, 29% of the students in the treatment group report receiving visits from other children to do personal studies and homework. These children come mostly from the same school and do this to be assisted by their classmates. This behavior might lead to positive spillovers, in particular, in terms of educational outcomes and also in terms of health (if students in the control group spend less time doing homework at home using the kerosene lamp). It is also possible that there are educational spillover effects other than from sharing the light if students in the treatment group study more and this leads to more learning by their peers. All of this would lead us to underestimate the impacts on learning outcomes.

[27] There could also be spillover effects of light ownership itself: households in the control group may be more likely to buy a light on their own from having seen one in use in a treated household. This form of spillover effect will not lead to any bias in our estimates, since our IV approach takes light ownership in the control group into account.

3 Results

3.1 Price Elasticity of Demand

This subsection analyzes how price (and reduced transaction and information costs) affect take-up at baseline and ownership of a working solar light at the time of the endline survey. Figure 2 shows that take-up strongly responds to price. The blue dots display the share of households that took or bought a basic solar light through our intervention in each treatment arm (free, and vouchers for USD 4, 7, or 9) and the corresponding solid blue line shows elasticity of demand, regressing voucher prices on take-up rates. Based on the exogenous price variation between the different voucher groups, we estimate the price semi-elasticity of demand at 0.5, that is, for a 1% increase in price, take-up drops by 0.5 percentage points.[28] 30.6% of participants who are given a voucher to purchase the light at the market price of USD 9 return to the school to purchase the light. The fact that this share is sizeable indicates that information and transaction costs present an important barrier to purchasing the lights outside of the intervention.[29] Take-up grows to 39.9% for those who receive a voucher with a co-pay of USD 7 and 69.5% for a co-pay of USD 4. In the free group, take-up is 100%. The difference in take-up between the free light and the one for USD 4 is, therefore, a combination of reduced transaction costs and reduced price.[30]

To measure the impact of having a solar light, we care not only about who takes a light but also about who owns one at the time of the endline survey (i.e., seven months after the distribution of the lights). The green triangles in Figure 2 show the share of households that own a working solar light at endline (obtained through the study or otherwise). Treatment assignment has a strong impact on ownership. Those offered a free basic light have a 40.8 percentage points higher ownership than those offered a light at market price, and 63.3 higher than the control group (of which 17.4% have a working solar light at the time of the endline survey).[31]

[28] To estimate the elasticity of demand, we only include the voucher treatments, not the free lights, since across the voucher treatments, the only thing that varies is price.

[29] To purchase a solar light on their own, people often need to travel. 31.9% of participants who already owned a solar light at baseline bought it at the closest market and 12.8% in another town.

[30] The fact that vouchers could only be redeemed 4 to 6 weeks later might have reduced the price elasticity, as it gave households more time to come up with the money. Dupas (2009) finds that demand for bednets fell less steeply with price when households were given more time to raise the money to purchase them.

[31] Based on the pre-analysis plan, we also analyze whether households with higher kerosene expenditure at baseline are more likely to purchase a solar light. Table A.1 shows that this is not the case.

3.2 Light Usage

Solar Light Usage Does Not Differ Across Treatment Arms

Next, we analyze whether solar light usage, conditional on owning a light, differs across treatment arms, as described in Section 2.4. Table 2 shows these results for solar light usage on the day and the week preceding the endline survey. For both guardians and students, the corresponding F-test shows no significant heterogeneity and there is no positive correlation between the price and usage.

Solar Light Usage Does Not Decrease over Time

The sensors installed in a subset of solar lights allow us to track their usage over time. Figure 3 depicts results from these sensor data. Some sensors become inactive over time (shown by the red dotted line). The rate at which sensors become inactive is higher than the rate at which lights become inactive since the sensors themselves often break even when the light still works.[32] Conditional on the sensor still being active, usage is remarkably constant over time. The light is used, on average, on 6.87 days a week (solid blue line), for 4.27 hours per day (dashed green line), with no decrease over time.[33]

Impact on Light Usage

Next, we analyze whether the solar light replaces other lighting sources or whether they are used in addition (i.e., "stacking"). Table 3 shows effects of owning a working solar light on lighting use by guardians (Panel A) and students (Panel B). Total light use increases for students (by about 0.4 hours per day, compared to a control complier mean (CCM) of 3.2 hours) but not for guardians (Column 1). Having a solar light almost fully replaces the use of one kerosene-fueled lamp in the household (Column 2). In addition, the solar light also leads to more consistent lighting. Households with a working solar light are 39 percentage points less likely to have experienced a lighting interruption in the preceding month, in which they have to sit in the dark because they ran out of fuels, batteries or other energy sources, compared to a CCM of 48%) (Column 3). The most frequently cited reason for lighting

[32] The breakage rate of the lights themselves is 1.15% per month, which we discuss in more detail in Section 3.3 about abatement costs.

[33] It is also interesting to note that there is no systematic difference between sensor data and self-reported data on light use, conditional on the sensor working. For more details see (Rom et al., 2020).

interruptions is lack of money to buy fuel or batteries (77%). Since solar lights do not rely on such energy sources, they can provide more reliable lighting.

In terms of hourly light use, we also see a clear shift: both guardians and students spend more time with solar lights being the main source of lighting and less time with kerosene-fueled lights being the main source of lighting (Columns 4–7). This change shift is at the source of the impacts of the intervention on kerosene consumption, emissions, and health, which we now turn to.

3.3 Environmental Impacts

Kerosene Consumption

As a result of the reduced use of kerosene lights discussed above, there is a strong reduction in kerosene consumption. Column (8) in Table 3 shows that households purchase 1.3 fewer liters of kerosene in the month preceding the endline survey, a 50% reduction. Annualized, this corresponds to approximately 16 fewer liters of kerosene purchased per household. This reduction in kerosene consumption has both environmental benefits in terms of greenhouse gas emissions and private benefits in terms of household budgets. We next discuss the impact on emissions and then turn to the private benefits in Section 3.4.

Emissions

As discussed in the background section, how much emissions one liter of kerosene emits depends on the type of light used. To estimate the intervention's impacts on emissions, we therefore multiply each household's reduction in kerosene purchases with the emissions generated by the type of light that household uses.[34] Table 4 shows the resulting reduction in monthly emissions: 81.8g of BC, $2,882$g of CO_2, and 85.0g of $PM_{2.5}$. In terms of reduction in CO_2-eqs, this implies a reduction of $71,296$g per month (using the central estimate of the conversion factor from BC to CO_2-eqs (Bond et al., 2011)). Given the uncertainty surrounding the CO_2-eq calculations by climate scientists (as described in the background section), we also show impacts on CO_2-eqs using a number of alternative conversion factors, in Table A.2, row 2. We will turn to these alternative estimates again below.

[34]For the 19.4% of households that use both kerosene lanterns and tin lamps, we assume that they use half of the kerosene for each type of light.

CO_2 Abatement Costs per Ton of CO_2-eq Reduction

Based on these results, we can estimate the abatement costs of reducing CO_2-eq emissions through this intervention. We analyze the abatement costs for the free lights, and then discuss how results may change when selling the lights.

In addition to knowing the emissions reduction per working light, we need to estimate the likelihood of a light still working at any given point in time. Our data only allow us to measure the breakage rate between the light distribution and the endline survey.[35] In what follows, we assume that the breakage rate is constant over time. This implies a monthly breakage rate b of 1.15%. Since the assumption of a constant breakage rate becomes increasingly speculative when looking at the longer term, our main estimates of the abatement costs focus on the emissions reduction in the first two years.[36]

To get to the net reduction in CO_2-eq emissions, we deduct the CO_2-eq emissions embedded in the production of the lights. Based on Alstone et al. (2014) and Dones et al. (2003), a conservative estimate of embedded emissions is 49.6 kg of CO_2-eq.[37] The embedded emissions are low compared to the reduction of CO_2-eq emissions from the reduced kerosene burning. The total net reduction of CO_2-eqs over two years through the free distribution of solar lights is, therefore, $1,371$ kg of CO_2-eqs for the basic and $1,365$ kg of CO_2-eqs for the larger light.[38] Given the retail prices of USD 9 for the basic and USD 24 for the larger light, the abatement costs per ton of CO_2-eq emissions averted through free distribution of the lights is, therefore, USD 6.56 and USD 17.60 for the basic and larger solar light respectively. When thinking about a scale-up of this intervention, institutions that distribute free lights at a large scale could likely pay a lower whole sale price, which would lead to even lower abatement costs.

One question that may arise is whether it is more cost-effective to distribute the lights for free or to sell them with co-pay. The answer to this question may differ by whether one

[35]Since the lights with a sensor break more often as a result of the post-production appending of the sensor, we only include households that received a light with no sensor in this analysis. We do not use a separate breakage rate for the basic and larger light since there is no statistically significant difference between the two.

[36]The true evolution of the breakage rate could be increasing or decreasing over time. If some lights come with production faults and break very early on, while the others last long, the breakage rate would decrease early on. If materials become increasingly brittle over time, breakage rates may grow.

[37]This estimate is conservative in the sense that it assumes that all parts of the lights are produced with coal energy from inefficient power plants in China.

[38]This is the combined effect of a reduction of 9.13 kg of CO_2 and 1.63 kg of BC for the basic light, and of 7.89 kg of CO_2 and 1.62 kg of BC for the larger light.

considers all costs to society or only the costs to the policymaker or institution that sells or distributes the lights. From society's perspective, free distribution is clearly more cost effective. The cost of the light itself stays the same and, as we have seen in section 3.2, the usage of the light and therefore the emissions reductions are not affected by the amount of the co-pay by recipient households.[39] However, selling lights (via vouchers or otherwise) entails a higher implementation cost than free distribution, as it requires an entire system of collecting and monitoring the payments.

When focusing on the environmental cost-benefit analysis from a donor's or policymaker's perspective, however, distribution with co-pay by recipients may lead to higher emissions reduction per dollar invested than free distribution. Whether this will be the case in any particular setting depends both on the price elasticity of demand for the lights and the size of the fixed and variable administrative costs of free distribution vs. selling of the lights.

Even when using the higher retail prices, as we do in our intervention, the abatement costs per ton of CO_2-eq averted are far below the social cost of carbon (SCC) for both the basic and the larger light. The U.S. Environmental Protection Agency (EPA) recommended using an SCC estimate of USD 190 per ton of CO_2 (at a 2% discount rate) (U.S. Environmental Protection Agency, 2022).[40] In the European Union's carbon market, the price of a ton of CO_2 was around 80€ in November 2023 (Trading Economics, 2023). The abatement cost estimates of our intervention also compare favorably to other programs to reduce CO_2 emissions. The IEA (2022) estimates an average global cost of USD 32.98 per ton of abated CO_2-eq through all types of solar PV.[41]

Based on the measures of the SCC and the estimated reduction of CO_2-eq emissions from having access to a solar light, we can calculate the social benefit of our intervention. We estimate a social value of USD 260 based on the SCC estimates of the EPA and USD

[39] From the society's perspective, whether the light is paid for by a donor or (in full or in part) by the households is simply a redistribution of the costs, not a change in the total project cost.

[40] The EPA calculates the SCC for different discount rates (1.5%, 2%, and 2.5%), resulting in estimates of USD 340, USD 190, and USD 120, respectively. In its most recent Circular on the issue, the US government recommended the use of the 2% discount rate (Office of Management and Budget, 2023).

[41] However, this comparison may underestimate the average climate impact of solar technology interventions, as some of the included projects may also lead to reductions in BC, which are not taken into account in the IEA (2022) abatement cost estimate. One aspect that makes it likely that solar lights will lead to higher reductions in CO_2-eq per dollar invested than larger solar installations is that their electricity is used exclusively for lighting, replacing polluting kerosene lamps, while the more expensive larger installations are often also used for other purposes and additional electricity consumption, which does not lead to crowd out carbon-based energy sources.

120 based on the EU's carbon price. However, because carbon markets do not include BC emissions (so far), carbon credits from the carbon markets cannot be used to pay for this intervention.

As mentioned above, abatement cost estimates depend on the conversion factor of BC to CO_2-eqs, and these can vary due to uncertainties of BC's global warming potential, based on the climate science literature. To analyze the robustness of our estimates, Table A.2 shows abatement cost estimates using a broad range of conversion factors from that literature. In addition, the table also shows abatement costs when taking emissions reductions beyond the first two years into account. Across all these estimates, even the most conservative (using a low conversion factor and taking only the first two years of emissions reduction into account) leads to an abatement cost of USD 44.00 per ton of CO_2-eq averted, which is still significantly below the current SCC estimates. Overall, our results therefore show that distributing solar lights is a very cost-effective way to reduce CO_2-eq emissions.

3.4 Private Benefits

Next, we analyze the private benefits of the solar lights in terms of energy expenditures, health, education, and psychological well-being.

Energy Expenditures

Table 5 shows the impacts on total energy expenditure and its components separately for the larger and basic light. Overall, monthly energy expenditures fall by USD 1.3 for the basic light and USD 2.4 for the larger light (compared to a CCM of USD 4.2). The main reason the larger light has a bigger impact on energy expenditures is that it also enables phone charging. We see a corresponding reduction of USD 0.9 in phone charging expenditures (compared to a CCM of USD 1.1).[42] Based on these estimates of the reduction in monthly energy expenditures e, we can calculate the net present value (NPV) of getting a solar light. To calculate the NPV, we use a monthly interest rate of $r = 0.075$, based on the cheapest commonly available credit at the time,[43] and a monthly breakage rate b of 0.0115, as discussed above. The NPV is then $e * \frac{1}{1-\frac{1-b}{1+r}}$. This results in an NPV of expenditure savings of USD 16.14 for the basic and USD 29.82 for the larger light. This expenditure reduction is higher

[42] We also find that about a third of households that received the larger light let non-household members charge their phone with it. This was not something the households charged money for (Table A.3).

[43] M-Shwari, a widely used mobile banking product for digital loans.

than the market price of these lights, which was USD 9 and USD 24, respectively. The NPV including net of cost of the light is 7.14 for the basic and 5.82 for the larger light, and the lights pay off after 9 and 19 months, respectively.[44]

Health

In addition to the financial benefits, households may also experience health benefits as a result of the reduction of $PM_{2.5}$ emissions in the home. We analyze this using standardized questions to measure respiratory and eye health symptoms, based on Lee et al. (2002), the European Community Respiratory Health Survey II, and Bates et al. (2013), respectively.[45] Following Bates et al. (2013), we summarize these outcomes in two indexes, ranging from 1–6 for eye-related symptoms and 0–5 for respiratory symptoms (expressed in standard deviations based on the distribution of the control group).

Table 6 shows the impact on these indexes for guardians and students. There are significant improvements both in terms of respiratory and eye health, for both guardians and students. Treatment effects range between 0.15 and 0.27 standard deviations.

Education

Access to better lighting may also help increase students' learning as it may allow them to spend more time doing homework after dark. Table 7 shows education-related outcomes. We find that indeed, access to a functioning solar light increases homework completion (Columns 1 and 2), homework done after dark (Column 3), as well as time spent in school (Column 5).[46] Nevertheless, there is no effect on test scores nor on the probability of participating in the exams for both the regular end-of-term school exams and the national primary school graduation exam (KCPE) for students in grade 8 (Columns 6 - 9).[47] We also find no impacts on test participation and test scores looking at subgroups by students' gender and pre-treatment school performance (Table A.5).

A key potential reason why we may not find any significant impacts on test scores might be spillovers to the control group. This would be consistent with Hassan and Lucchino

[44]Looking only at the first two years (similarly to what we did above when discussing environmental impacts), the NPV is USD 5.16 and USD 2.16 for the larger and basic light, respectively.

[45]The Data Appendix lists the specific questions used.

[46]In terms of type of light used for doing homework, Table A.4 shows that students with access to a working solar light are more likely to use the solar lights as their main source of lighting, and less likely to rely on tin lamps or kerosene lanterns for this activity.

[47]Table A.6 shows results separately by subjects.

(2016) who find positive within-school educational spillovers of access to a solar light. This would imply that the learning outcomes for students in our control group might have also improved, leading to a downward bias in our estimates of the impact on learning.

We therefore cannot rule out that the solar lights did improve learning and test scores. On the other hand, it is also possible that in our setting, differently from Hassan and Lucchino (2016), there were no positive impacts on learning despite the longer time spent on school work, potentially as a result of the reduction of sleep by almost half an hour (Column 10).

Psychological Well-being

Previous research has shown that access to energy can also affect psychological outcomes (Lee et al., 2020). Table 8 shows different psychological measures, all in standard deviations. We measure a range of different but related concepts (8 for guardians, 5 for students). Column (1) shows that averaging across all of them, there is a significant positive impact for both students by 0.11 and guardians by 0.07 standard deviations, respectively. For individual measures, we find significant improvements in guardians' assessment that their life as an adult will be better than it was for their parents (Column 3) and the perception that their economic situation improved over the previous three months (Column 8).

3.5 Other Outcomes

In addition to the variables discussed above, we specified the following outcomes in the pre-analysis plan: time use of guardians, attitudes towards aid for poor households, and safety. With regard to guardians' time use, we find no statistically significant effects other than an increase in sleep duration of about 18 minutes (Table A.7, Column 1).[48] We study participants' attitudes on who should provide for the needs of poor families (the families themselves vs. others) to address a common concern that distributing free items may affect such attitudes. We find no impact for either guardians or students (Appendix Table A.9). Finally, we also find no improvements on safety, neither in terms of guardians' subjective

[48]While we cannot be certain what led to this change (which goes in the opposite direction of the sleep changes for students), it could potentially be due to better sleep due to improved psychological outcomes and reduced financial expenditures; better sleep as a result of the health improvements, particularly breathing; or reduced need to work to cover energy expenditures (this would be consistent with the reduction in time spent working, which has a similar magnitude but is not statistically significant (Column 4)). Consistent with the change in reported sleep duration, we find that guardians go to sleep earlier and wake up later, while students go to sleep later and wake up earlier, though none of these are statistically significant (Appendix Table A.8).

feelings of safety at night inside or outside the home, nor on fire hazards or burn injuries (Table A.10).

3.6 Robustness Checks

This section discusses attrition and presents the main results for robustness separately by treatment arms and without gender-fixed effects.

Attrition

As discussed in the Data section above, there is slightly lower attrition in the treatment group than in the control group. In the following, we therefore show a descriptive analysis of attritors, and robustness checks accounting for differential attrition using Lee-bounds (Lee, 2009) and Inverse Probability Weighting (Wooldridge, 2002, 2007). As we will see, results are highly robust to these adjustments.

Table A.11 shows attrition probabilities across treatment arms. For guardians in the control group, the attrition rate is 8.3%. This rate is 2.3 percentage points lower for those in the treatment group (controlling for school and respondent gender fixed effects, as in all our regressions). Since our first stage outcome variable (whether the household owns a working solar light) is collected in the guardian survey, our estimation sample includes only the $1,313$ households in which the guardian took the endline survey. Among this estimation sample, there is also some attrition in the student endline survey. For outcome variables based on the student survey, the estimation is therefore somewhat smaller. The student attrition rate within our main estimation sample is (7.4%) for the control group, and 1.8 percentage points higher for the treatment group (not statistically significantly different). For completeness, we will still show robustness analysis accounting for student attrition below.

Table A.12 displays characteristics of attritors compared to non-attritors for the same variables that are also included in Table 1, which analyzes balance across treatment arms. For both students and guardians, attrition is higher when the guardian is not the student's parent (likely because settings in which the primary caregiver is not a parent are less stable and the primary caregiver may have changed or moved since the baseline survey). Among students, attritors are, in addition, more likely to have characteristics that tend to be associated with school dropout: lower grades, older age, and being female.

Table A.13 presents our main outcomes adjusted for attrition. Columns (2) and (3) provide Lee bounds Lee (2009). This approach provides upper and lower bounds of the estimates under extreme assumptions about the (unobserved) outcomes of attritors.[49] For most outcomes for which we find significant impacts in our main analysis, both upper and lower bounds remain statistically significant and qualitatively similar to the original estimates (shown in Column 1). Two exceptions are guardian respiratory health, for which the upper Lee bound is no longer statistically significant, and the guardian psychological index, for which the lower bound is no longer significant. Column (4) of Table A.13 shows results after applying inverse probability weighting (IPW) following Wooldridge (2002) and Wooldridge (2007). This approach re-weights the sample to re-balance observable characteristics across treatment groups to compensate for the differential attrition. Weights are based on a propensity score that calculates each observation's probability of being a non-attritor, using observable characteristics.[50] Each observation is then weighted with the inverse of this probability. This results in participants with characteristics that are underrepresented among non-attritors compared to attritors being given more weight. All of the main results that were statistically significant in our main analysis remain so after applying IPWs, with the exception of the student psychological index, which is no longer statistically significant.

Results by Treatment Arm and Without Gender Fixed Effects

In our main results above, we show analyses of the impact of solar lights pooled across all treatment arms, except for energy expenditures, where we find different effects for the larger and basic lights. For completeness, Appendix Tables A.14 and A.15 show the impact estimates for all our main results separately by type of light and for each treatment arm. Table A.14 confirms that there is no statistically significant difference in the mean treatment effects for the basic and solar light, with the exception of energy expenditures. Table A.15 shows all treatment arms separately. Given the smaller sample size in each treatment arm, all estimates are of course more noisy, but we see no systematic differences and cannot reject the null hypothesis of equal effects across all treatment arms for any of the main outcomes.

[49]Specifically, we trim the sample of the groups with less attrition such that the share of remaining observations (after attrition plus trimming) is equal to the treatment arm with the least attrition (i.e., the control group). To estimate the lower and upper bounds, the trimming is done in two different ways: once by removing the observations with the largest values of the outcome, and once by removing the observations with the smallest values of the outcomes. The estimates using these trimmed samples provide the Lee bounds.

[50]We include the same characteristics in the calculation of the propensity score as in the balance of randomization table (Table 1).

As discussed, all estimates above include gender fixed effects, due to differences in gender shares across treatment effects. Appendix Table A.16 shows our main results without correcting for this imbalance. All results are qualitatively similar.

4 Conclusion

In light of the challenge to expand access to modern electricity while ensuring environmental sustainability, solar lights could be an economical step towards achieving several goals at once. They provide a more reliable, cheaper, and healthier lighting source to the 750 million people who still live without a connection to an electric grid. Given current trends in expansion of access to the electric grid, energy poverty will likely remain pressing for several decades to come, particularly in regions where grid expansion is not financially cost-effective, in rural areas in low- and middle-income countries. At the same time, the solar lights have a strong impact on carbon emissions, in particular when considering the large climate impact of black carbon, and the low costs of these lights.

While solar lights can of course only be a small part of the solution for both energy poverty and climate change, they may provide a highly cost-effective medium-turn intervention that makes a tangible contribution to reduce climate change while at the same time improving the lives of some of the worlds' poorest families.

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Figures

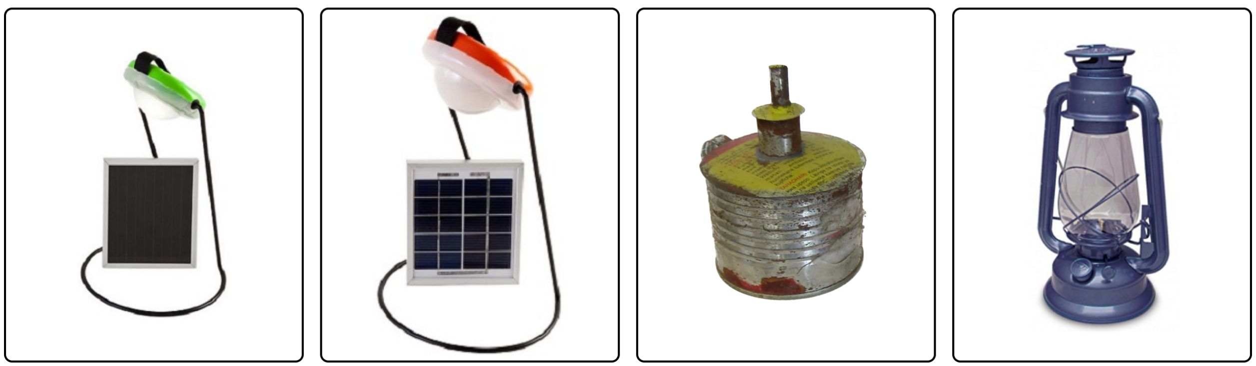
Figure 1: Intervention Design

Panel A: Control and Treatment Groups

Control	**Voucher**			**Free**	
No Light N=400 Households	Market Price 9 USD N=200 Households	Low Subsidy 7 USD N=201 Households	High Subsidy 4 USD N=209 Households	Basic Light Free N=200 Households	Larger Light Free N=200 Households

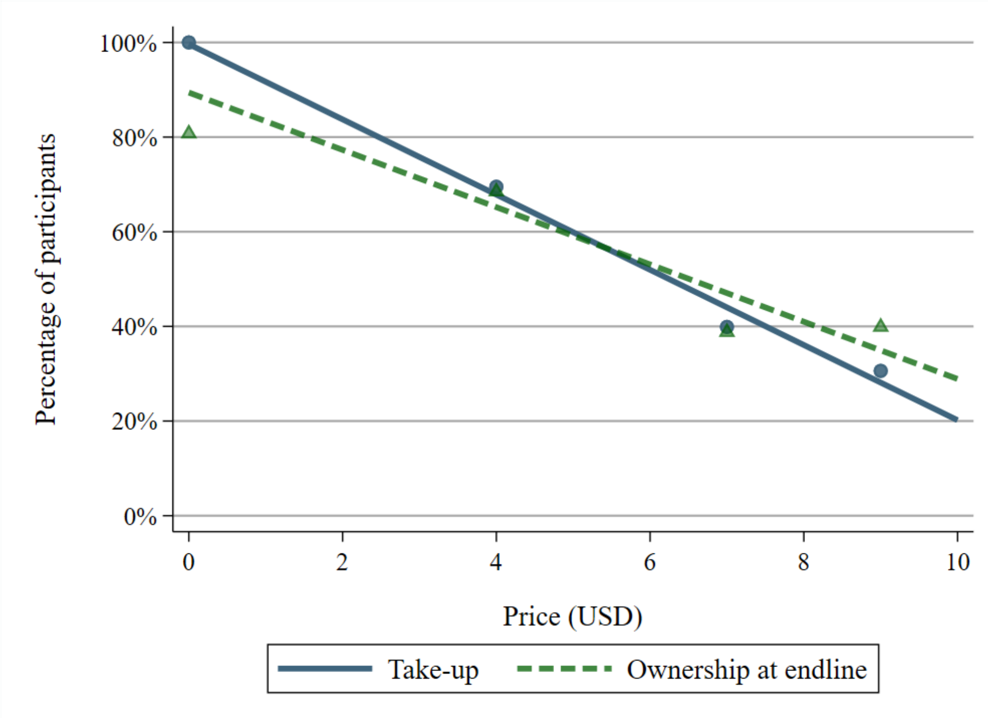
Panel B: Types of light

Basic Solar Light	**Larger Solar Light**	**Kerosene Tin Lamp**	**Kerosene Lantern**
Sun King Eco	Sun King Mobile		



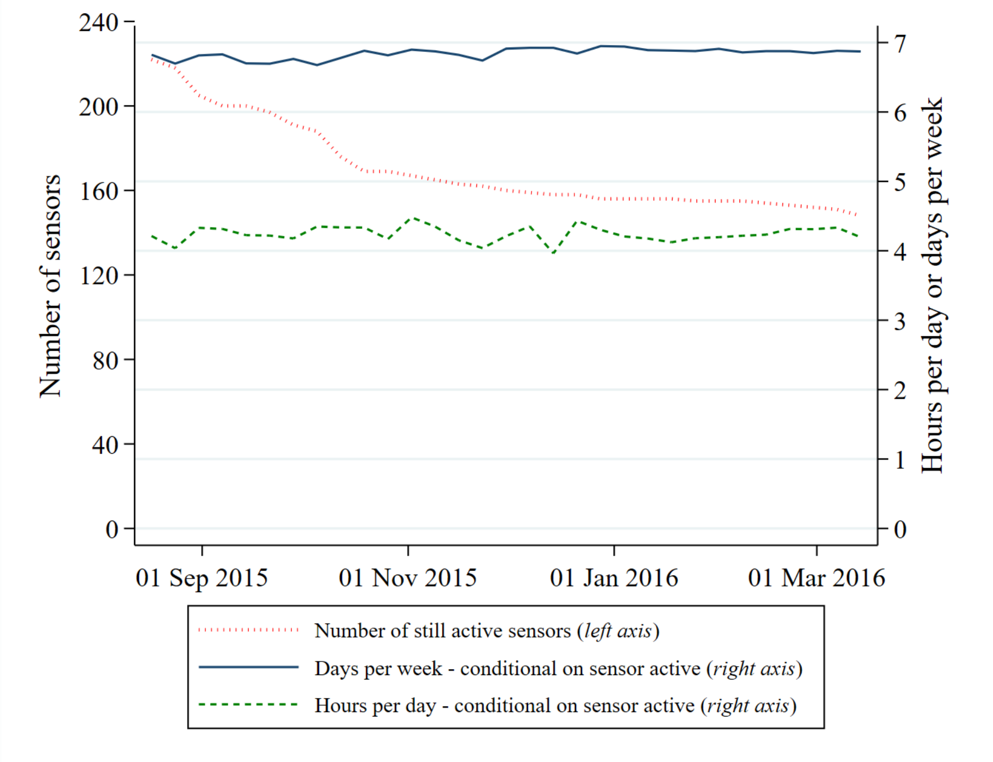
Notes: Panel A describes different treatment arms of the randomized intervention. Panel B displays the two types of solar lights that were distributed through the study and the two types of kerosene lights most commonly used prior to treatment.

Figure 2: Take-up and Endline Ownership of the Basic Solar Light by Price



Notes: This figure shows take-up and endline ownership of the basic solar light for the prices of the different treatment arms (free, and vouchers to purchase a light for USD 4, 7, or 9). Blue dots show the share of participants who took or bought a light through the intervention. Green triangles show the share who owned any working solar light at the time of the endline survey. The solid blue and dashed green lines stem from regressions of voucher prices on take-up and endline ownership, respectively. (These regressions do not include free lights, since the voucher distribution differs from free lights in other ways than just price.)

Figure 3: Solar Light Usage as Measured by Sensors



Notes: This figure plots weekly solar light usage, based on sensors' measurement, from the third week of August to the third week of March 2016. The dotted red line shows the evolution of the number of active sensors. Sensors are considered active from the first to the last week in which the sensor indicates that the light was turned on. The decay over time can therefore stem from sensors breaking, lights breaking, or lights otherwise no longer being used. The solid blue and dashed green lines show the mean days per week and mean hours per day a solar light was used, conditional on having an active sensor.

Tables

Table 1: Balance of Randomization

		Difference to the control mean					
		Treatment arms					Pooled
	(1) Control mean	(2) Free basic	(3) High subsidy	(4) Low subsidy	(5) Market price	(6) Free larger	(7) All treatments
Connection to the grid	0.013	0.003	0.015	0.002	-0.003	-0.008	0.002
	[0.112]	(0.009)	(0.013)	(0.010)	(0.010)	(0.008)	(0.006)
Household owns a solar light	0.053	0.018	0.006	0.006	-0.001	0.007	0.007
	[0.224]	(0.024)	(0.023)	(0.016)	(0.021)	(0.023)	(0.017)
Household size	6.76	-0.178	0.088	0.253	0.265	-0.045	0.071
	[2.18]	(0.199)	(0.204)	(0.218)	(0.186)	(0.225)	(0.148)
Household practices agriculture	0.992	0.002	-0.002	-0.008	-0.018^{*}	-0.007	-0.006
	[0.087]	(0.005)	(0.008)	(0.009)	(0.009)	(0.012)	(0.005)
Student is in grade 5	0.372	0.023	-0.065^{*}	-0.048	-0.038	-0.017	-0.029
	[0.484]	(0.030)	(0.033)	(0.038)	(0.043)	(0.036)	(0.023)
Student is in grade 6	0.355	-0.020	0.058	0.021	0.049	0.025	0.026
	[0.479]	(0.043)	(0.043)	(0.040)	(0.039)	(0.040)	(0.025)
Student is in grade 7	0.273	-0.002	0.008	0.027	-0.011	-0.007	0.003
	[0.446]	(0.038)	(0.043)	(0.028)	(0.045)	(0.040)	(0.027)
Standardized average test scores	3.30	0.029	-0.012	-0.034	0.051	0.081	0.024
	[0.796]	(0.049)	(0.054)	(0.048)	(0.070)	(0.062)	(0.041)
Student's age	13.12	-0.090	0.073	0.122	0.191	0.021	0.060
	[1.73]	(0.170)	(0.170)	(0.147)	(0.208)	(0.162)	(0.122)
Student is female	0.568	-0.087^{*}	-0.011	-0.008	-0.001	-0.087^{*}	-0.040
	[0.496]	(0.043)	(0.035)	(0.045)	(0.036)	(0.042)	(0.029)
Guardian is female	0.639	0.003	0.076^{*}	0.051^{*}	0.037	0.076^{*}	0.048^{*}
	[0.481]	(0.047)	(0.043)	(0.029)	(0.055)	(0.037)	(0.026)
Guardian is student's parent	0.775	0.000	-0.000	-0.035	0.004	0.025	-0.001
	[0.418]	(0.027)	(0.033)	(0.041)	(0.025)	(0.037)	(0.023)
Guardian is student's grandparent	0.107	0.018	0.021	-0.009	-0.028	-0.022	-0.004
	[0.310]	(0.021)	(0.028)	(0.026)	(0.017)	(0.023)	(0.015)
Student from replacement list	0.135	0.005	-0.004	0.006	-0.022	-0.000	-0.003
	[0.342]	(0.027)	(0.022)	(0.035)	(0.027)	(0.028)	(0.019)
Baseline guardian survey at school	0.950	-0.010	-0.022	-0.013	-0.012	0.010	-0.009
	[0.219]	(0.014)	(0.020)	(0.018)	(0.025)	(0.015)	(0.009)
School FE		Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	400	200	209	201	200	200	1,010
P-value of F-test		0.993	0.619	0.952	0.387	0.268	0.724

Notes: This balance table shows baseline characteristics across treatment groups. Column (1) displays means and standard deviations for the control group. Each row then shows two separate regressions. Columns (2) to (6) of the baseline variable on treatment dummies for each treatment arm. Column (7) of the baseline variable on one dummy combining all treatment groups. Standardized average test scores are averaged across English, math, science, social studies, and Swahili. "Student from replacement list" indicates students that were added to the study from a randomized replacement list because the originally designated student was absent on the day of the baseline survey. Standard errors clustered at the school level in parentheses. Number of observations indicates households in each treatment group. F-test for the null hypothesis of joint significance across all variables in each column (using a stacked regression with bootstrapped p-values and standard errors additionally clustered at the household level). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Usage of Solar Lights

	Hours yesterday		Days past week	
	Guardians	Students	Guardians	Students
	(1)	(2)	(3)	(4)
Free basic light	3.15***	2.41***	6.44***	6.62***
	(0.19)	(0.25)	(0.17)	(0.44)
High subsidy (USD 4)	3.41***	2.32***	6.80***	5.92***
	(0.22)	(0.24)	(0.10)	(0.45)
Low subsidy (USD 7)	3.51***	2.69***	6.63***	6.29***
	(0.64)	(0.51)	(0.32)	(1.12)
Market price (USD 9)	2.63***	1.29**	6.45***	4.00***
	(0.56)	(0.53)	(0.38)	(1.12)
Free larger light	3.40***	2.19***	6.84***	5.76***
	(0.19)	(0.20)	(0.10)	(0.45)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Number of observations	1,249	1,202	1,253	1,203
P-value of F-test	0.592	0.272	0.148	0.262

Notes: This table shows impact estimates of having a working solar light on solar light usage by treatment arm, following the specification described under "Usage" in Section 2.4. Columns (1) and (3) show results from the guardian endline survey; Columns (2) and (4) from the student endline survey. Standard errors clustered at the school level in parentheses. F-test for the null hypothesis of equal impacts by all treatment arms (using a stacked regression with standard errors additionally clustered at the household level). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Impact on Light and Kerosene Usage

	(1) Total light usage yesterday (hours)	(2) Number of kerosene-fueled lights used last month	(3) Light interruption last month (probability)	(4) Solar light as main light source yest. (hours)	(5) Tin lamp as main light source yest. (hours)	(6) Kerosene lantern as main light source yest. (hours)	(7) Other light as main light source yest. (hours)	(8) Kerosene purchased last month (liters)
Panel A: Guardians								
Solar light	−0.207	−0.998***	−0.385***	2.100***	−1.811***	−0.267***	−0.229***	−1.278***
	(0.144)	(0.093)	(0.046)	(0.131)	(0.112)	(0.056)	(0.080)	(0.228)
Control complier mean	3.196	2.453	0.476	0.007	2.510	0.306	0.373	2.558
Number of observations	1,313	1,312	1,286	1,313	1,313	1,313	1,313	1,299
Panel B: Students								
Solar light	0.390***			3.393***	−2.815***	−0.204*	0.009	
	(0.114)			(0.178)	(0.218)	(0.100)	(0.068)	
Control complier mean	3.225			0.000	3.193	0.272	0.139	
Number of observations	1,203			1,203	1,203	1,203	1,203	
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows impact estimates of having a working solar light on light and kerosene usage, following Equations (1) and (2). Panel A shows outcomes from the guardian and Panel B from the student endline survey. "Other" in Column 7 includes electricity-powered lighting, firewood, battery-powered torches/lanterns, candles, pressurized kerosene lanterns, other rechargeable lanterns, and cell phone lighting. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Impact on Household Emissions

	(1) BC emissions (g/month)	(2) CO_2 emissions (g/month)	(3) CO_2-eq emissions (g/month)	(4) $PM_{2.5}$ emissions (g/month)
Solar light	-81.84^{***}	$-2,882^{***}$	$-71,296^{***}$	-85.04^{***}
	(14.67)	(532)	(12,776)	(15.24)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Control complier mean	161.91	5,653	141,013	168.19
Number of observations	1,291	1,291	1,291	1,291

Notes: This table shows impact estimates of having a working solar light on household emissions, following Equations (1) and (2). Column (1) reports black carbon and Column (2) CO_2 emissions. Column (3) shows CO_2-eq emissions of Columns (1) and (2) combined, and Column (4) particulate matter $PM_{2.5}$ emissions. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Impact on Monthly Household Energy Expenditures

	(1) Total expenditure	(2) Kerosene	(3) Phone charging	(4) Firewood	(5) Batteries	(6) Charcoal	(7) Electricity bill	(8) Other
Basic light	−1.299***	−0.702***	0.162	−0.390**	0.016	−0.013	−0.269	−0.104
	(0.397)	(0.156)	(0.127)	(0.165)	(0.069)	(0.304)	(0.257)	(0.111)
Larger light	−2.401***	−0.903***	−0.858***	−0.093	0.131	−0.113	−0.424	−0.140
	(0.469)	(0.081)	(0.076)	(0.198)	(0.077)	(0.255)	(0.289)	(0.082)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	4.211	1.821	1.143	0.369	0.274	0.211	0.362	0.033
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
P-value of F-test	0.053	0.241	0.000	0.112	0.248	0.767	0.564	0.625

Notes: This table shows impact estimates of having a working solar light on households' monthly energy expenditures in USD, following Equations (1) and (2). Coefficients in each row stem from a separate regression by type of light. Column (1) shows total energy expenditure, Columns (2) to (8) report its different components. "Other" includes candles, generator fuel, liquefied petroleum gas, sawdust, dung/charcoal mixture, and others. Standard errors clustered at the school level in parentheses. F-test for the null hypothesis of equal impacts by both types of light (using a stacked regression with standard errors additionally clustered at the household level). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Impact on Health

	Eyes		Respiratory	
	Guardians (1)	Students (2)	Guardians (3)	Students (4)
Solar light	-0.228^{***}	-0.244^{**}	-0.153^{**}	-0.270^{*}
	(0.075)	(0.090)	(0.069)	(0.135)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Control complier mean	1.484	1.427	0.907	1.114
Number of observations	1,313	1,203	1,313	1,203

Notes: This table shows impact estimates of having a working solar light on health outcomes, following Equations (1) and (2). Columns (1) and (2) display an index of eye-related symptoms such as dryness, grittiness, redness, etc., and Columns (3) and (4) an index of respiratory-related symptoms such as shortness of breath, asthma, cough, etc., following Bates et al. (2013) and The European Community Respiratory Health Survey II Steering Committee (2002). Higher values indicate more symptoms. All outcomes expressed in standard deviations of the control group. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Impact on Education Inputs and Outcomes

	(1) Completed homework every day last week	(2) Share of days with complete homework last week	(3) Share of days homework after dark last week	(4) Homework and personal study (hours yesterday)	(5) Time in school (hours yesterday)	(6) Average score of 5 school exams	(7) Average KCPE score	(8) Participated in school exam	(9) Participated in KCPE exam	(10) Sleep (hours yesterday)
Solar light	0.153***	0.079***	0.111***	0.317	0.545*	−0.085	−0.087	0.032	−0.088	−0.438**
	(0.032)	(0.018)	(0.037)	(0.193)	(0.277)	(0.096)	(0.172)	(0.031)	(0.092)	(0.173)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	0.649	0.843	0.723	2.415	4.047	3.413	4.407	0.782	0.666	8.433
Number of observations	1,051	1,051	1,051	1,203	1,203	1,012	236	1,313	371	1,203

Notes: This table shows impact estimates of having a working solar light on education inputs and outcomes, following Equations (1) and (2). Columns (1) to (5) and (10) are reported by students; Columns (6) to (9) are based on administrative test score records. Column (6) reports average school exam scores in March 2016 and Column (7) average test scores in the national high school graduation exam KCPE, among students in grade 8 who participated in this exam (in control group standard deviations). Columns (8) and (9) show the probability that a student participated in the March 2016 school exams and that grade 8 students participated in the KCPE, respectively. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table A.5 shows heterogeneity of these estimates by gender and by school performance at baseline. Table A.6 shows the effects on test scores separately by subject.

Table 8: Impact on Psychological Outcomes

Panel A: Outcomes of guardians

	(1) Average of outcomes	(2) Future holds good things	(3) Future better than parents'	(4) In charge of own destiny	(5) Most people can be trusted	(6) Happiness	(7) Life satis-faction	(8) Economic situation improved	(9) Not at risk of depression
Solar light	0.072*	−0.025	0.191**	0.035	−0.082	0.099	−0.060	0.282**	0.136
	(0.040)	(0.100)	(0.070)	(0.097)	(0.085)	(0.082)	(0.102)	(0.112)	(0.128)
Control complier mean	2.123	3.847	2.550	2.466	0.362	3.811	2.102	1.113	0.735
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313

Panel B: Outcomes of students

	(1) Average of outcomes	(2) Future holds good things	(3) Future better than parents'	(4) Able to do things as well as others	(5) On the whole satisfied with self	(6) Rarely feeling no good at all			
Solar light	0.111**	0.028	0.101	0.153	0.120	0.154			
	(0.047)	(0.076)	(0.099)	(0.112)	(0.086)	(0.091)			
Control complier mean	3.019	4.209	5.314	2.332	1.307	1.936			
Number of observations	1,203	1,203	1,203	1,203	1,203	1,203			
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows impact estimates of having a working solar light on psychological outcomes of guardians (Panel A) and students (Panel B), following Equations (1) and (2). Column (1) shows the average of the variables in the other columns. Columns (2) and (3) show the extent to which respondents agree (scale 1-4) with the statement that their future holds good things, and that their life as an adult will be better than it was for their parents. For Columns (4) and upward, questions are different for students and guardians. Panel A Column (4) shows the extent to which guardians believe that individuals can decide their own destiny vs. it being is impossible to escape a predetermined fate (scale 1-10). Column (5) shows a dummy of whether guardians think most people can be trusted. Column (6) displays self-reported happiness (scale 1-4) and Column (7) life satisfaction (scale 1-10). Column (8) shows guardians' assessment of how their economic situation changed over the previous 3 months (scale 1-5) and Column (9) displays a measure of depression based on a series of questions from the CES-D scale (inverted, such that a positive number represents a low risk of depression). Panel B Columns (4)-(6) shows the impact on students' agreement (scale 1-4) with the statement that they are able to do things as well as most other people, that they are satisfied with themselves, and that at times they think they are no good at all (inverted, such that a positive number means low agreement). All outcomes expressed in standard deviations of the control group. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendices

A Appendix Tables

Table A.1: Baseline Kerosene Expenditure and Take-Up

	(1) Take-up	(2) Take-up	(3) Take-up
Kerosene expenditures at baseline in USD	0.006 (0.007)		
Kerosene expenditures at baseline in log (USD)		0.008 (0.032)	
Kerosene expenditures at baseline above median			-0.011 (0.031)
School FE	Yes	Yes	Yes
Treatment arm FE	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes
Number of observations	564	564	564

Notes: This table shows estimates from a regression of take-up on kerosene expenditures during the week prior to the baseline survey in among participants in the voucher treatment arms (for which take-up is a choice). Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: Impact on Emissions:
Different CO_2-eq Conversion Factors and Time Horizons

	(1) CO_2-eq SFP East Africa	(2) CO_2-eq SFP East Africa lower bound	(3) CO_2-eq SFP East Africa upper bound	(4) CO_2-eq GWP 100	(5) CO_2-eq GWP 100 lower bound	(6) CO_2-eq GWP 100 upper bound
Conversion factor	836	371	1,300	900	120	1,800
Reduction in CO_2-eq per light (kg) per month	68.2	31.8	104	73.2	12.2	144
Reduction in CO_2-eq per light (kg) over 2 years	1,371	613	2,127	1,475	205	2,941
Abatement cost per ton of CO_2-eq (USD)	6.57	14.7	4.23	6.10	44.0	3.06
Reduction in CO_2-eq per light (kg) over 5 years	2,881	1,319	4,441	3,097	475	6,121
Abatement cost per ton of CO_2-eq (USD)	3.12	6.83	2.03	2.91	19.0	1.47
Reduction in CO_2-eq per light (kg) over 10 years	4,343	2,001	6,680	4,665	736	9,198
Abatement cost per ton of CO_2-eq (USD)	2.07	4.50	1.35	1.93	12.2	0.978
Reduction in CO_2-eq per light (kg) infine time horizon	5,863	2,710	9,010	6,297	1,009	12,400
Abatement cost per ton of CO_2-eq (USD)	1.53	3.32	0.999	1.43	8.92	0.726

Notes: This table shows estimates for the reduction in CO_2-eq emissions per household and the cost per ton of CO_2-eqs abated in USD for the basic solar light when distributed for free. Columns (1) to (3) show the conversion factor for East Africa based on the concept of the Specific Forcing Pulse (SFP) (over 100 years) from Bond et al. (2011), and its upper and lower bounds. Columns (4)-(6) show the Global Warming Potential (GWP) estimate (over 100 years) from Bond et al. (2013), and its upper and lower bound. Row 1 shows the respective values of the BC conversion factor that we use to calculate CO_2-eq emission reductions. Row 2 shows the estimated monthly reduction of CO_2-eq emissions per household, equivalent to the impact of the basic light on CO_2-eq emissions shown in Column (2) in Appendix Table A.14. Subsequent rows show the estimated CO_2-eq reductions for different lamp lifespans and their respective estimated cost per ton of CO_2-eq abated, in USD. We show estimates for 2 years, 5 years, 10 years, and an infinite time horizon. Calculations are based on a monthly breakage rate of 1.15%.

Table A.3: Impact on Guardians' Provision of Phone Charging Services

	(1) Letting others charge their phones at home or business	(2) Generating income from letting others charge their phone
Free basic light	-0.082^{*}	-0.026
	(0.040)	(0.032)
High subsidy (USD 4)	-0.045	-0.019
	(0.066)	(0.048)
Low subsidy (USD 7)	-0.190	-0.062
	(0.130)	(0.093)
Market price (USD 9)	-0.077	-0.095
	(0.122)	(0.077)
Free larger light	0.313^{***}	0.022
	(0.052)	(0.027)
School FE	Yes	Yes
Respondent gender	Yes	Yes
Control complier mean	0.000	0.004
Number of observations	1,018	1,018
P-value of F-test	0.000	0.378

Notes: This table shows impact estimates of having a working solar light on guardians' provision of phone charging services by treatment arm. The first stage instruments the probability of owning a working solar light with each treatment assignment while the second stage simultaneously estimates the effect of each treatment arm using a stacked regression, as described in Section 2.4. Outcomes are binary indicators of whether phone charging services are provided (Column 1) and if any income is generated from these services (Column 2). Standard errors clustered at the school level in parentheses. F-test for the null hypothesis of equal impacts by all treatment arms (using a stacked regression with standard errors additionally clustered at the household level). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Impact on Students' Light Usage for Homework

	(1) Mostly use solar light for homework	(2) Mostly use tin lamp for homework	(3) Mostly use kerosene lantern for homework
Solar light	1.040***	−0.878***	−0.109***
	(0.054)	(0.048)	(0.032)
School FE	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes
Control complier mean	0.000	0.865	0.126
Number of observations	1,051	1,051	1,051

Notes: This table shows impact estimates of having a working solar light on students' light usage while doing homework during the week before the endline survey, following Equations (1) and (2). Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5: Impact on Education:
Heterogeneous Effects by Gender and Baseline School Performance

	(1) Completed homework every day last week	(2) Share of days with complete homework last week	(3) Share of days homework % after dark last week	(4) Homework and personal study (hours yesterday)	(5) Time in school (hours yesterday)	(6) Average score of 5 school exams	(7) Average KCPE score	(8) Participated in school exam	(9) Participated in KCPE exam	(10) Sleep (hours yesterday)
Panel A: Heterogeneous effects by gender										
Solar light	0.198***	0.089**	0.148**	0.541**	0.813*	-0.197	-0.095	0.035	0.005	-0.735**
	(0.059)	(0.034)	(0.057)	(0.257)	(0.441)	(0.157)	(0.253)	(0.058)	(0.167)	(0.276)
Solar light × female	-0.078	-0.017	-0.073	-0.408	-0.508	0.200	0.022	-0.004	-0.162	0.562
	(0.074)	(0.043)	(0.064)	(0.401)	(0.514)	(0.161)	(0.270)	(0.087)	(0.188)	(0.326)
Female	0.021	0.000	0.031	0.127	0.348	-0.120	-0.135	-0.006	0.024	-0.374*
	(0.043)	(0.026)	(0.043)	(0.226)	(0.344)	(0.082)	(0.201)	(0.046)	(0.097)	(0.200)
Control complier mean	0.604	0.834	0.685	2.190	3.779	3.525	4.415	0.779	0.573	8.730
Number of observations	1,051	1,051	1,051	1,203	1,203	1,012	236	1,313	371	1,203
P-value of F-test	0.006	0.004	0.099	0.658	0.338	0.967	0.667	0.539	0.068	0.403
Panel B: Heterogeneous effects by school performance at baseline										
Solar light	0.237***	0.107***	0.064	0.489*	0.784**	0.006	-0.204	0.055	0.006	-0.419
	(0.054)	(0.028)	(0.064)	(0.276)	(0.313)	(0.065)	(0.335)	(0.061)	(0.154)	(0.300)
Solar light × $> 50^{th}$ perc.	-0.126	-0.035	0.066	-0.431	-0.640*	-0.208	0.091	-0.091	-0.182	0.119
	(0.093)	(0.031)	(0.097)	(0.322)	(0.315)	(0.179)	(0.394)	(0.085)	(0.202)	(0.361)
$> 50^{th}$ percentile.	0.059	0.017	-0.058	0.361*	0.534***	0.704***	0.933***	0.132***	0.428***	-0.288
	(0.068)	(0.027)	(0.059)	(0.194)	(0.172)	(0.118)	(0.223)	(0.045)	(0.112)	(0.193)
Control complier mean	0.576	0.822	0.773	2.256	3.734	3.319	4.544	0.767	0.574	8.436
Number of observations	959	959	959	1,092	1,092	935	226	1,187	355	1,092
P-value of F-test	0.079	0.007	0.043	0.804	0.657	0.223	0.598	0.492	0.192	0.089
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table examines the same outcomes presented in Table 7 in terms of heterogeneity by gender (Panel A) and baseline test scores (Panel B). $> 50^{th}$ percentile indicates that a student's average school exam score in March 2015 was above the sample median. F-tests for the null hypothesis that the sum of the first two coefficients (i.e. impact of solar lights on girls, and impact of solar lights for students above the median, respectively) is different from zero. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.6: Impact on Students' Test Scores

	(1) Swahili	(2) Math	(3) English	(4) Science	(5) Social studies	(6) Average score
Panel A: School exams						
Solar light	-0.096	0.022	-0.087	-0.159	-0.027	-0.085
	(0.114)	(0.106)	(0.121)	(0.099)	(0.122)	(0.096)
Number of observations	1,010	1,004	1,009	1,004	1,004	1,012
Panel B: KCPE exam						
Solar light	-0.019	0.232	-0.196	-0.193	-0.256	-0.087
	(0.206)	(0.229)	(0.203)	(0.218)	(0.196)	(0.172)
Number of observations	236	236	236	236	236	236
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows test score results from Table 7, separately for each of the 5 compulsory subjects. Panel A shows school exam scores from March 2016. Panel B shows test scores from the national high school graduation exam KCPE, among students in grade 8 who participated in this exam. All outcomes expressed in standard deviations of the control group. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: Impact on Time Use of Guardians

	(1) Sleep	(2) Social and recreational activities	(3) Household and care work	(4) Work	(5) Travel
Panel A: Activities over the entire day					
Solar light	0.295*	0.396	−0.357*	−0.352	0.122
	(0.155)	(0.397)	(0.206)	(0.440)	(0.135)
Control complier mean	8.554	5.873	4.586	4.245	0.634
Number of observations	1,313	1,313	1,313	1,313	1,313
Panel B: Activities between 7pm and 7am					
Solar light	0.345***	−0.153	−0.048	−0.113	−0.016
	(0.120)	(0.119)	(0.098)	(0.066)	(0.032)
Control complier mean	8.390	1.873	1.067	0.556	0.096
Number of observations	1,313	1,313	1,313	1,313	1,313
School FE	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes

Notes: This table shows impact estimates of having a working solar light on guardians' time use (in hours) the day before the endline survey, following Equations (1) and (2). Panel A refers to time use over the entire day. Panel B includes only activities during times when it is dark, i.e. between 7pm and 7am. Columns (2) to (5) are aggregated categories based on more detailed activities, as discussed in the data appendix. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8: Impact on Time at Which Participants go to Sleep and Wake Up

	(1) Guardian going to sleep	(2) Guardian waking up	(3) Student going to sleep	(4) Student waking up
Solar light	−0.068	0.035	0.078	−0.112
	(0.111)	(0.082)	(0.066)	(0.085)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Control complier mean	19.375	3.977	21.479	5.947
Number of observations	1,290	1,286	1,172	1,181

Notes: This table shows impact estimates of having a working solar light on the time at which guardians (Columns 1 and 2) and students (Columns 3 and 4) go to sleep and wake up on the day before the endline survey, following Equations (1) and (2). A negative coefficient indicates an earlier time, a positive coefficient a later time. Standard errors clustered at the school level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.9: Impact on Attitude of Who Should Provide for the Poor

	(1) Guardians	(2) Students
Solar light	−0.042	0.056
	(0.081)	(0.064)
School FE	Yes	Yes
Respondent gender	Yes	Yes
Control complier mean	2.602	2.730
Number of observations	1,313	1,203

Notes: This table shows impact estimates of having a working solar light on attitudes about who should provide for the needs of poor families, following Equations (1) and (2). Possible responses are 1–only the poor family itself; 2–the poor family should provide a lot and others should provide a little; 3–the poor family should provide a little and others should provide a lot; or 4–only others should provide for them. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: Impact on Safety

	(1) Feeling safe inside the home at night (guardian)	(2) Feeling safe outside the home at night (guardian)	(3) Number of fire hazards in home past 3 months	(4) Any household member had burn injury past 3 months	(5) Number of adults with burn injury past 3 months	(6) Number of children with burn injury past 3 months
Solar light	−0.040	−0.003	−0.020	−0.007	0.005	−0.012
	(0.086)	(0.088)	(0.015)	(0.010)	(0.004)	(0.009)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	3.207	2.956	0.024	0.021	0.000	0.022
Number of observations	1,312	1,250	1,313	1,313	1,313	1,313

Notes: This table shows impact estimates of having a working solar light on several dimensions of safety, following Equations (1) and (2). Columns (1) and (2) show categorical variables taking values of 1 (never), 2 (sometimes), 3 (usually), and 4 (always) of perceived safety at night inside and outside the home, respectively. Column (3) shows the reported number of times there was a fire hazard in the home in the past three months. Column (4) indicates whether any household member received any burn injuries in the past three months. Columns (5) and (6) report the number of adults and children who were injured during the occurrences from Column (4), respectively. Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.11: Attrition Probabilities

	(1) Endline attrition guardians	(2) Endline attrition guardians	(3) Endline attrition students	(4) Endline attrition students
All treatments	-0.023^{*}		0.018	
	(0.013)		(0.016)	
Free basic light		-0.018		-0.007
		(0.021)		(0.022)
High subsidy (USD 4)		-0.033		0.025
		(0.020)		(0.026)
Low subsidy (USD 7)		-0.014		0.030
		(0.016)		(0.029)
Market price (USD 9)		-0.010		0.036
		(0.017)		(0.021)
Free larger light		-0.039^{**}		0.009
		(0.018)		(0.024)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Control mean	0.083	0.083	0.074	0.074
Number of observations	1,410	1,410	1,313	1,313

Notes: This table shows estimates of having a working solar light on attrition probability by each treatment arm. For all treatments, the first and second stage follow Equations (1) and (2) For individual treatments, the first stage instruments the probability of owning a working solar light with each treatment assignment while the second stage simultaneously estimates the effect of each treatment arm using a stacked regression, as described in Section 2.4. Columns (1) and (2) show the probability that guardians did not take part in the endline survey. Columns (3) and (4) show the same outcome for students. Standard errors clustered at both the school and household level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.12: Attrition by Baseline Characteristics

	Guardian attrition		Student attrition	
	(1) Non - attritors	(2) Difference attritors	(3) Non - attritors	(4) Difference attritors
Connection to the grid	0.014	-0.003	0.015	-0.007
	[0.119]	(0.010)	[0.121]	(0.009)
Household owns a solar light	0.058	0.027	0.060	-0.021
	[0.234]	(0.023)	[0.237]	(0.016)
Average test scores (baseline)	3.32	-0.022	3.34	-0.271***
	[0.786]	(0.066)	[0.788]	(0.062)
Student is in grade 5	0.343	0.032	0.344	-0.018
	[0.475]	(0.053)	[0.475]	(0.047)
Student is in grade 6	0.374	-0.036	0.377	-0.033
	[0.484]	(0.053)	[0.485]	(0.042)
Student is in grade 7	0.283	0.004	0.279	0.051
	[0.451]	(0.035)	[0.449]	(0.052)
Student is female	0.542	-0.034	0.530	0.141**
	[0.498]	(0.040)	[0.499]	(0.056)
Student's age	14.17	0.00	14.07	1.20***
	[1.75]	(0.00)	[1.69]	(0.154)
Guardian respondent is student's parent	0.792	-0.225***	0.807	-0.171***
	[0.406]	(0.039)	[0.395]	(0.042)
Guardian respondent is student's grandparent	0.104	-0.019	0.098	0.070**
	[0.306]	(0.028)	[0.298]	(0.029)
Guardian respondent is female	0.672	0.009	0.673	-0.014
	[0.470]	(0.059)	[0.469]	(0.039)
Student from replacement list	0.132	0.043	0.133	-0.021
	[0.338]	(0.034)	[0.340]	(0.026)
Baseline guardian survey at school	0.947	-0.052	0.949	-0.036
	[0.225]	(0.041)	[0.219]	(0.028)
Household size	6.82	-0.042	6.83	-0.141
	[2.15]	(0.250)	[2.14]	(0.195)
Household performs agricultural activities	0.988	0.003	0.989	-0.018
	[0.110]	(0.013)	[0.103]	(0.014)
School FE		Yes		Yes

Notes: This table shows results from OLS estimates where endline attrition is regressed on baseline characteristics from Table 1. Columns (1) and (3) show means and standard deviations for guardian and student non-attritors. Columns (2) and (4) show the difference between non-attritors and attritors for guardians and students, respectively. Standard errors clustered at the school level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.13: Main Impacts:
Robustness Check I: Attrition Adjustments

	Non-adjusted estimates	Lee Bounds: Lower bound	Lee Bounds: Upper bound	Inverse Probability Weighted
	(1)	(2)	(3)	(4)
Kerosene purchased last month	-1.278^{***}	-1.457^{***}	-1.176^{***}	-1.420^{***}
	(0.228)	(0.232)	(0.237)	(0.259)
CO_2-eq emissions	$-71,296^{***}$	$-81,603^{***}$	$-66,184^{***}$	$-80,719^{***}$
	(12,776)	(13,209)	(13,509)	(14,346)
Total monthly energy expenditure	-1.871^{***}	-2.386^{***}	-1.732^{***}	-1.901^{***}
	(0.334)	(0.410)	(0.350)	(0.404)
Guardian eye health	-0.228^{***}	-0.336^{***}	-0.157^{*}	-0.253^{***}
	(0.075)	(0.069)	(0.085)	(0.077)
Student eye health	-0.244^{**}	-0.261^{**}	-0.243^{**}	-0.301^{***}
	(0.090)	(0.103)	(0.091)	(0.087)
Guardian respiratory health	-0.153^{**}	-0.290^{***}	-0.094	-0.123^{*}
	(0.069)	(0.074)	(0.088)	(0.069)
Student respiratory health	-0.270^{*}	-0.306^{**}	-0.271^{*}	-0.279^{*}
	(0.135)	(0.123)	(0.135)	(0.139)
Student homework completion	0.153^{***}	0.150^{***}	0.157^{***}	0.177^{***}
	(0.032)	(0.032)	(0.033)	(0.034)
Student school exam scores	-0.096	-0.103	-0.087	0.122
	(0.098)	(0.087)	(0.091)	(0.219)
Average of psychological outcomes (guardians)	0.072^{*}	0.022	0.125^{***}	0.082^{*}
	(0.040)	(0.041)	(0.041)	(0.043)
Average of psychological outcomes (students)	0.111^{**}	0.112^{**}	0.118^{**}	0.093
	(0.047)	(0.050)	(0.048)	(0.054)

Notes: This table examines the robustness of the main results by accounting for differential attrition at endline. Each row shows impact estimates of having a working solar light on the main outcomes of the study, following Equations (1) and (2). Column (1) displays the main baseline estimates. Columns (2) and (3) report lower and upper bound estimates using Lee-bounds (Lee, 2009). Column (4) shows adjusted estimates using Inverse Probability Weights (IPW) obtained from probit estimates using baseline characteristics (Wooldridge, 2002, 2007). Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.14: Main Impacts:
Robustness Check II: Separate Estimates by Basic vs. Larger Light

	(1) Kerosene purchased last month (liters)	(2) CO_2-eq emissions (g/month)	(3) Total monthly energy expenditure (USD)	(4) Eye health guardians (s.d.)	(5) Eye health students (s.d.)	(6) Respiratory health guardians (s.d.)	(7) Respiratory health students (s.d.)	(8) Completed homework every day last week (prob.)	(9) Average score of 5 school exams (s.d.)	(10) Psycho-logical index guardians (s.d.)	(11) Psycho-logical lndex students (s.d.)
Basic light	-1.262^{***}	$-68,204^{***}$	-1.299^{***}	-0.263^{**}	-0.236^{**}	-0.167^{*}	-0.260^{*}	0.170^{***}	-0.134	0.069	0.103
	(0.298)	(16,751)	(0.397)	(0.107)	(0.096)	(0.093)	(0.150)	(0.044)	(0.135)	(0.054)	(0.065)
Larger light	-1.198^{***}	$-67,929^{***}$	-2.401^{***}	-0.221^{**}	-0.282^{**}	-0.124	-0.239	0.136^{***}	-0.050	0.057	0.107^{*}
	(0.220)	(11,943)	(0.469)	(0.101)	(0.135)	(0.090)	(0.168)	(0.045)	(0.072)	(0.050)	(0.057)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	2.558	141,013	4.211	1.484	1.427	0.907	1.114	0.649	3.413	2.123	3.019
Number of observations	1,299	1,291	1,313	1,313	1,203	1,313	1,203	1,051	1,012	1,313	1,203
P-value of F-test	0.801	0.984	0.053	0.770	0.729	0.729	0.896	0.577	0.418	0.853	0.957

Notes: This table examines the robustness of the main results by separately estimating the impact of each type of light. It shows impact estimates of having a working solar light on the main outcomes of the study, following Equations (1) and (2). Each row shows a separate regression by type of light. Standard errors clustered at the school level in parentheses. F-test for the null hypothesis of equal impacts by both types of light (using a stacked regression with standard errors additionally clustered at the household level). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.15: Main Impacts:
Robustness Check III: Separate Estimates by Treatment Arm

	(1) Kerosene purchased last month (liters)	(2) CO_2-eq emissions (g/month)	(3) Total monthly energy expenditure (USD)	(4) Eye health guardians (s.d.)	(5) Eye health students (s.d.)	(6) Respiratory health guardians (s.d.)	(7) Respiratory health students (s.d.)	(8) Completed homework every day last week (prob.)	(9) Average score of 5 school exams (s.d.)	(10) Psycho-logical index guardians (s.d.)	(11) Psycho-logical Index students (s.d.)
Free basic light	−1.292***	−68,535***	−1.418***	−0.248**	−0.248*	−0.152	−0.219	0.147**	−0.207	0.072	0.079
	(0.305)	(18,573)	(0.345)	(0.118)	(0.120)	(0.124)	(0.135)	(0.056)	(0.141)	(0.059)	(0.078)
High subsidy (USD 4)	−1.125**	−61,236**	−1.255	−0.317*	−0.250*	−0.139	−0.271	0.191***	−0.058	0.032	0.148*
	(0.453)	(23,722)	(0.773)	(0.167)	(0.131)	(0.157)	(0.210)	(0.061)	(0.154)	(0.070)	(0.082)
Low subsidy (USD 7)	−0.169	−4,698	−2.141	−0.152	−0.859*	0.221	0.054	0.158	−0.464	−0.103	0.270
	(1.273)	(80,130)	(1.841)	(0.446)	(0.428)	(0.435)	(0.421)	(0.247)	(0.293)	(0.263)	(0.232)
Market price (USD 9)	−0.658	−25,125	−2.100	−0.943**	0.004	−0.268	0.201	0.076	0.035	−0.094	−0.070
	(0.682)	(40,807)	(1.935)	(0.357)	(0.624)	(0.411)	(0.494)	(0.255)	(0.251)	(0.174)	(0.224)
Free larger light	−1.198***	−67,929***	−2.401***	−0.221**	−0.282*	−0.124	−0.239	0.136***	−0.050	0.057	0.107*
	(0.220)	(11,957)	(0.470)	(0.101)	(0.135)	(0.090)	(0.168)	(0.045)	(0.072)	(0.050)	(0.057)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	2.558	141,013	4.211	1.484	1.427	0.907	1.114	0.649	3.413	2.123	3.019
Number of observations	1,299	1,291	1,313	1,313	1,203	1,313	1,203	1,051	1,012	1,313	1,203
P-value of F-test	0.587	0.443	0.222	0.256	0.418	0.835	0.667	0.874	0.380	0.859	0.566

Notes: This table examines the robustness of the main results by separately estimating the impact of each treatment arm. It shows impact estimates of having a working solar light on the main outcomes of the study. The first stage instruments the probability of owning a working solar light with each treatment assignment while the second stage simultaneously estimates the effect of each treatment arm using a stacked regression, as described in Section 2.4. Standard errors clustered at the school level in parentheses. F-test for the null hypothesis of equal impacts by all treatment arms (using a stacked regression with standard errors additionally clustered at the household level). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.16: Main Impacts:
Robustness Check IV: Estimates Excluding Gender Fixed Effects

	(1) Kerosene purchased last month (liters)	(2) CO_2-eq emissions (g/month)	(3) Total monthly energy expenditure (USD)	(4) Eye health guardians (s.d.)	(5) Eye health students (s.d.)	(6) Respiratory health guardians (s.d.)	(7) Respiratory health students (s.d.)	(8) Completed homework every day last week (prob.)	(9) Average score of 5 school exams (s.d.)	(10) Psycho-logical index guardians (s.d.)	(11) Psycho-logical lndex students (s.d.)
Solar light	-1.321^{***}	$-73,255^{***}$	-1.957^{***}	-0.220^{***}	-0.249^{**}	-0.133^{*}	-0.280^{*}	0.155^{***}	-0.084	0.070	0.115^{**}
	(0.220)	(12,417)	(0.328)	(0.074)	(0.092)	(0.071)	(0.137)	(0.031)	(0.096)	(0.040)	(0.047)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	No	No	No	No	No	No	No	No	No	No	No
Control complier mean	2.601	142,972	4.297	1.476	1.432	0.887	1.124	0.647	3.412	2.126	3.015
Number of observations	1,299	1,291	1,313	1,313	1,203	1,313	1,203	1,051	1,012	1,313	1,203

Notes: This table examines the robustness of the main results by excluding gender-fixed effects. It shows impact estimates of having a working solar light on the main outcomes of the study, following Equations (1) and (2). Standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Research Design

We conducted a randomized control trial (RCT) between June 2015 and March 2016 that consisted of the distribution of solar lights among 5th, 6th, and 7th grade students of 20 primary schools located in Nambale and Teso South, two sub-counties of the Busia county in Western Kenya.[51] Out of the seven sub-counties in Busia, we selected these two for the following reasons. First, both counties have a large fraction of people living in rural areas, which often have less access to electricity. Second, they were not part of an electrification pilot program run by the Kenyan government at the time. Third, there were no other studies in either of the two places that would have interfered with our intervention. Finally, our policy partner (SolarAid) worked in these areas, and both counties were reachable from their field offices. This appendix outlines the different stages of the intervention summarized in Figure B.1. See Figure B.2 for a detailed timeline of the study.

B.1 Pre-Baseline

School selection: We selected schools from a list of 127 schools (50 from Nambale and 77 from Teso South) provided by the Ministry of Education. We removed urban schools since these areas often have better access to electricity. Among the rural schools, four did not provide information on the number of students and were thus excluded. Subsequently, we removed schools with less than 200 students, private schools, boarding schools, unisex schools, schools for children with special needs, those schools too far away to be reached within one day from the field office, and five schools that were already part of other projects. We randomly ordered the pool of 97 remaining eligible schools and selected the first 20 schools (10 in each sub-county) to participate in the intervention. We recruited these schools by attending a monthly meeting of all head teachers (teachers who are designated to have a management role) in the sub-counties at which the research team provided information about solar lights. After the meeting, we asked the selected head teachers to take part in the study.[52] Table B.1 shows the final list of schools that participated in the intervention.

Household and student selection: Upon identifying the sample of schools, we selected households that had at least one student enrolled in grades 5–7. Grades 1–4 were not included since it would have been hard for those students to answer survey questions on their own, while grade 8 was excluded since eighth graders would have left school before the study had ended. The field team visited the schools to gather the list of students in grades 5–7 within each school and to assess which students belonged to the same household. The final list resulted in 3,360 eligible households, from which we selected 1,410 to participate in the intervention. If households had more than one student in grades 5–7 (i.e., siblings), a single student was randomly selected while the other ones were replaced with students from a back-up household list.[53] Consequently, the intervention includes only one student per household.

[51] To distribute the lights, we partnered with SolarAid, a large Kenyan distributor of portable solar lights.

[52] Four head teachers did not attend the meeting so their schools were replaced with the following schools on the list in the respective sub-county.

[53] This back-up list was randomly assembled for each school from households that were originally not selected for the study in case it was necessary to fill in for students who were absent during the day of the baseline survey. The share of back-up students is balanced across treatment arms.

Randomization: Based on the final sample of students, we randomly assigned students within each school to either the control or the five different treatment arms described in Section 2.2. Thus, randomization was conducted at the household level and stratified at the school level by following the next steps. First, we randomly ordered all households within each school. Second, we assigned the first 40 households to the control group or the free solar light arms in an alternating order (starting with the control group). Among those receiving a free solar light, treatment alternated between the basic and larger solar lights (starting with the basic option).[54] Third, we assigned the 41st to 70th, 75th or 80th, depending on the school, ranked households to the rest of the treatment arms with an alternating pattern among the vouchers to purchase the basic solar light: high subsidy, low subsidy, and market price (starting with the high subsidy voucher).[55] Finally, the rest of the ranked households were kept to create the aforementioned back-up student list. For each selected household, we surveyed the student and one of the student's guardians.[56]

Implementation: The process of communicating the randomized treatment offers to participants was as follows. We designed a lottery game based on text messages to make it clear to guardians that whether they won a prize was decided by random chance.[57] As these types of text-message games are very common in Kenya, it was easy for guardians to understand.[58] The lottery worked in the following way: at the end of the baseline survey guardians were assigned a "lucky number" and surveyors invited them to participate in the lottery. Then, the guardians sent a text message with the "lucky number" to participate in the lottery and immediately received a text message back, announcing if they had either won a free solar light, had the opportunity to purchase one at a given price during the following weeks, or had not won anything. This text message could then be used to either receive a free solar light on the spot or a personalized voucher to be redeemed at a later date.

B.2 Baseline Surveys

Student survey: The student baseline survey was conducted at school and was scheduled on a specific day for each school in July and August 2015. Students originally selected to

[54] See Figure 1 for a description of the lights.

[55] For schools with at least 70 eligible students, this means that we selected 20 for the control group and 10 for each of the treatment arms. Two schools had less than 70 students who met the selection criteria, even though overall more than 200 students were enrolled, so we reduced the number of distributed vouchers to 0 (Sango) and to 10 (Aburi) in these schools. These are likely to be newer schools where most enrolled students were in younger grades. Consequently, we increased the number of selected students to 75 or 80 in larger schools in order to keep field operations as simple as possible. Table B.1 presents these numbers.

[56] Neither the randomization results nor process were disclosed to the head teachers or the study participants.

[57] This "lucky number" and the corresponding treatment assignment were determined in advance, but it appeared to participants that they were generated on the spot.

[58] Kenyan phone providers frequently send subscribers codes that they can submit via text message to participate in lotteries. After developing our process, we tested it in several pilots, discussed it with beneficiaries, and made sure the lottery was well understood by our participants. It turned out that this process had the advantage that people would intuitively understand that the allocation of prices was random and that what they answered in the survey would not have an impact on their chances of winning.

participate in the study were especially encouraged by the head teachers to attend school on the day of the survey. Students on the back-up list were not asked specifically to be present that day. 13.0% of students who were initially selected for the study did not attend school on the day of the baseline survey and were thus replaced by students from the back-up list.[59] During this survey, students were asked about their guardian's name and phone number, and to invite them to the interview at a specific date and time.[60]

Guardian survey: The guardian baseline survey was also conducted at school after the student survey in June and July 2015. During their interviews, students received paper slips with an invitation for the guardians, including a note stating that guardians would be reimbursed for travel costs and receive a participation gift. In some cases, the guardian who showed up at the interview differed from the one the student had listed.[61]

If the guardians did not attend the interview, surveyors would attempt to contact them to conduct the survey at home or at their workplace.[62] Head teachers also helped by telling students to remind their guardians about the survey.

Treatment arms announcement: At the end of the baseline survey, the different treatment offers were communicated to guardians as follows. Surveyors assigned guardians the "lucky number" to participate in a lottery. Guardians then participated in the lottery by sending a text message with the "lucky number", and immediately received a text message back, announcing whether they had not won anything, had won a free solar light, or had won the voucher to purchase a light at a given price during the following weeks. Surveyors showed the basic solar light to guardians who were offered the vouchers and read a script containing basic information about the light.[63]

Solar light redemption: Guardians belonging to the free treatment arms were offered their solar light directly at the end of their surveys at school or at home. Guardians in the voucher arms were offered the vouchers instead, which they could use within 4 to 6 weeks to purchase the light at the school (they could not purchase it on the same day).[64] The guardians were given dates and times when they could come back to the school to purchase the lamp.[65] In most cases, the guardians went back to school. In some cases the head teachers collected the orders from the guardians in several rounds, as well as the money and vouchers, and purchased the solar lights for them. In other cases, some participants went to *SunnyMoney* directly.

[59] The share of replacement students is balanced across treatment arms.

[60] 12 surveyed students who were initially assigned to receive a voucher (10) or a free lamp (2) did not receive their respective treatment because their guardians did not attend their baseline interview.

[61] For instance, the student may have mentioned one parent, but the other one showed up.

[62] To identify whether the guardian survey at baseline took place at school we used the date on which the survey was conducted as a proxy. If the actual date matches the scheduled date, we assume that the interview took place at school; if not, we assume it took place outside of school.

[63] This script is shown in the Data Appendix

[64] All vouchers contained the guardian's name and were not transferable. We later conducted audits to ensure that respondents did not sell or trade their vouchers.

[65] Granting a certain amount of time to people to redeem the voucher is the usual way *SunnyMoney* operates. Furthermore, this extra period might allow people to save enough money to purchase the light.

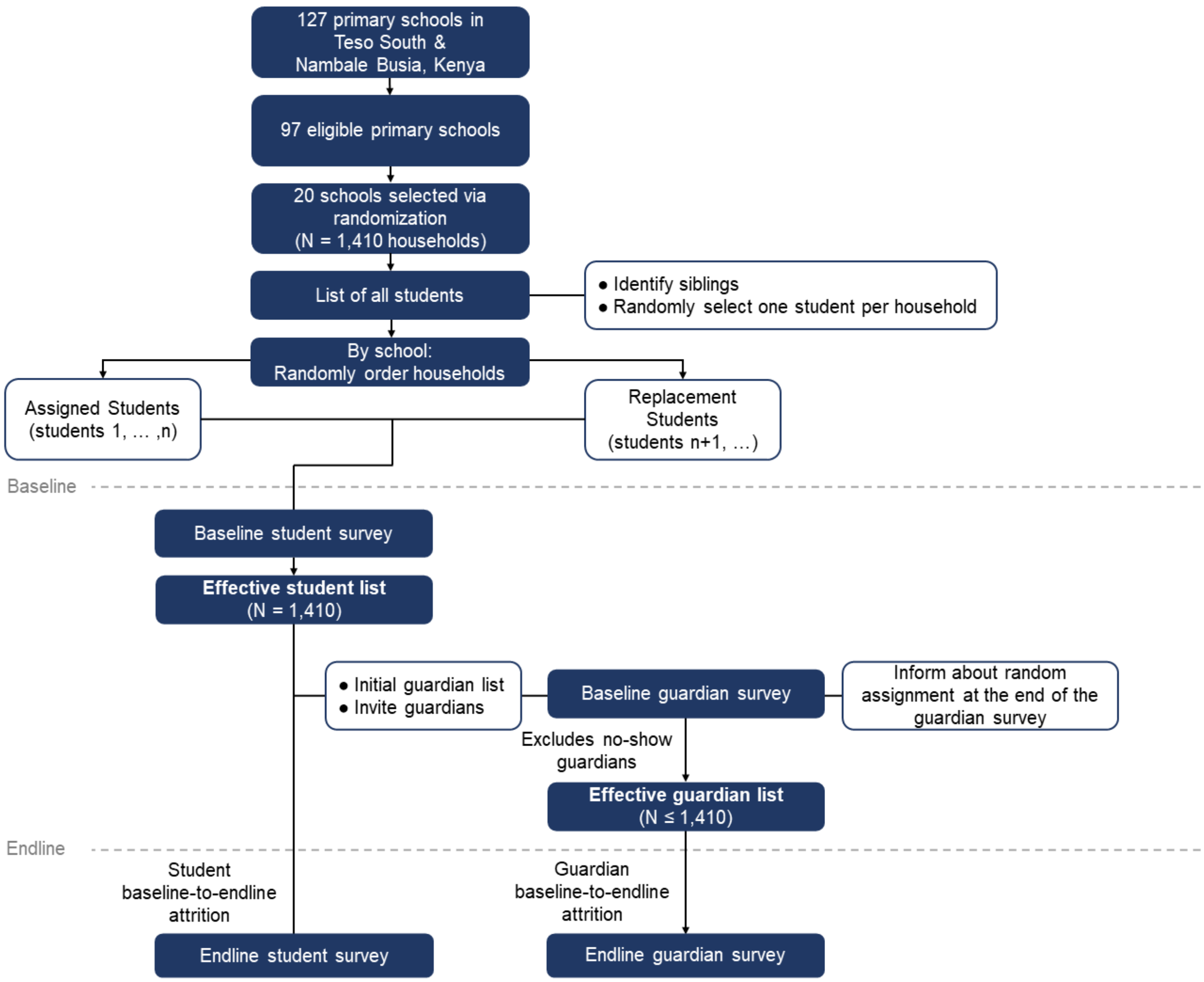
B.3 Endline Surveys

Student survey: Endline surveys of students were also conducted at school, who were again encouraged by the head teachers to attend school on the day of the survey. If the student was absent during that day, surveyors attempted to contact the guardians directly to encourage them to send the student to school for another survey attempt at a later date.[66]

Guardian survey: The endline guardian surveys were conducted at home. Surveyors tried to book appointments directly with the guardians and notified them before coming to their houses. For guardians without a phone number, surveyors went through the household's village elder to contact the guardians. Although surveyors intended to survey the same guardian that had been interviewed in the baseline, there were 22 cases in which the survey respondent changed. Nonetheless, the share of respondent changes is balanced across treatment arms.

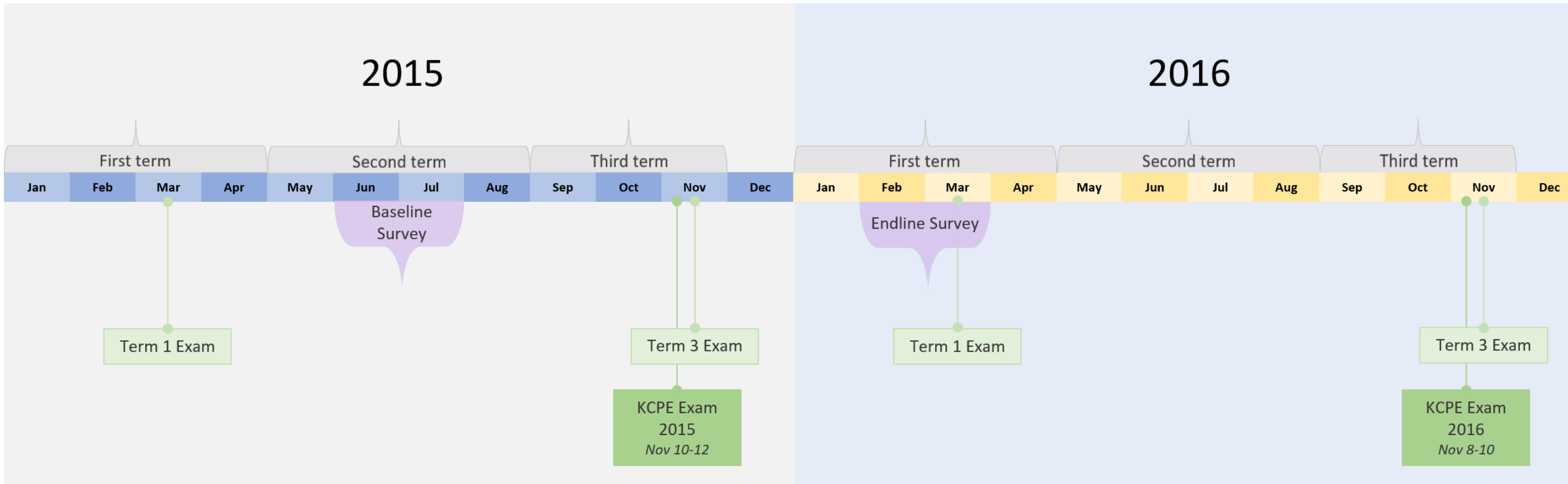
[66]Some students were found at their house, while others had moved to another school. Depending on their availability, an appointment was booked with them. If the parent was absent on the day of an at-home survey, then surveyors again attempted to coordinate another interview with them at home on a later date.

Figure B.1: Research Design and Survey Implementation



Notes: We received a list of 127 primary schools in the two sub-counties of Teso South and Nambale in Busia, Western Kenya. Based on this list, we identified 97 schools that met our eligibility criteria (rural areas, school size, public and mixed-gender schools, excluding special needs and boarding schools). From these schools, we randomly chose 20 schools and created a list of all students in grades 5-7. Randomization into treatment arms was conducted at the household level and stratified at the school level. We selected only one student per household. We then randomly ordered the students, creating a list of selected students and a back-up list. The treatment assignment follows a specific pattern of the students' ordering. We first surveyed students at the school and absent students were replaced with students from the back-up list. We then invited their guardians for another baseline survey that took place several days after the student survey. Households were informed about their treatment assignment at the end of the guardian baseline survey by a lottery game process.

Figure B.2: Timeline of the Intervention



Notes: Baseline surveys were conducted in June–July 2015, during the second term of the year (Capital News, 2014). The Term Exams took place in March and November of both 2015 and 2016 (Ministry of Education of Kenya, 2015). The KCPE Exams took place from the 10th to the 12th November 2015 (Kenya National Examinations Council, 2015) and from the 8th to the 10th November 2016 (Kenya National Examinations Council, 2016). The endline surveys were conducted February–March 2016, during the first term of the year (The Standard, 2015).

Table B.1: Households by School and Control or Treatment Arm

		Frequency by treatment arm						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sub county	School name	Control	Free Basic	High Subsidy	Low Subsidy	Market Price	Free Larger	All Treatments
Nambale	Malanga	20	10	10	10	10	10	70
Nambale	Lwanyange	20	10	10	10	10	10	70
Nambale	Emukhuyu	20	10	10	10	10	10	70
Nambale	Esidende	20	10	10	10	10	10	70
Nambale	Maolo	20	10	10	10	10	10	70
Nambale	Sianda	20	10	14	13	13	10	80
Nambale	Khayo	20	10	13	14	13	10	80
Nambale	Sango	20	10	0	0	0	10	40
Nambale	Opeduru	20	10	12	12	11	10	75
Nambale	Mwangaza	20	10	10	10	10	10	70
Teso South	Olepito	20	10	12	11	12	10	75
Teso South	Obekai	20	10	12	11	12	10	75
Teso South	Kaliwa	20	10	12	12	11	10	75
Teso South	Kamarinyang'	20	10	13	11	11	10	75
Teso South	Ong'aroi	20	10	12	11	12	10	75
Teso South	Asing'e	20	10	12	12	11	10	75
Teso South	Ng'elechom	20	10	13	11	11	10	75
Teso South	Akites	20	10	10	10	10	10	70
Teso South	Aburi	20	10	4	3	3	10	50
Teso South	Odiyoi	20	10	10	10	10	10	70
Total		400	200	209	201	200	200	1410

Notes: This table reports how many households (students) were randomly assigned to either control or each treatment arm within each of the twenty schools and two sub-counties included in the intervention. Initially, we selected 70 households with students in grades 5-7. However, two of the schools did not have enough households that met the selection criteria. In these two schools, we reduced the number of vouchers distributed to 0 (Sango) and to 10 (Aburi) and increased the number of sampled students in larger schools instead. To keep field operations as simple as possible, we increased participation to 75 (Opeduru, Olepito, Obekai, Kaliwa, Kamarinyang, Ong'aroi, Asinge, Ng'eechom) or 80 (Sianda, Khayo) in larger schools.