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

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Abstract

Both human-driven global climate change and the widespread energy poverty in low- and middle-income countries are among the most pressing challenges of our times. This paper analyzes an intervention that addresses both. Over 750 million people globally still lack access to electricity. Many of them use kerosene for lighting, a strong global warming pollutant. In addition, kerosene lights generate indoor air pollution and steep financial costs for the households. This paper presents experimental evidence from Kenya on the impact and cost-effectiveness of solar lighting in addressing these issues. We find that access to a solar light significantly reduces the use of kerosene-fueled lamps and thus CO_2 and black carbon emissions. In addition, we find substantial private gains for households, of almost 59% lower total household energy expenditures, and health improvements of about 0.25 standard deviations. While households gain private returns to buying a solar light, subsidies have a strong impact on take-up. Given the environmental externalities, distribution of free solar lights in areas with high use for kerosene lamps may therefore be one of the most a cost-effective intervention for CO_2 reduction, while at the same time increasing 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 half a billion people still have no access to electricity in their home. Many of them live in Sub–Sahara Africa, where only 47% of the population had home electricity in 2019 (Ritchie et al., 2020). An often-raised concern is that access to energy for these populations would jeopardize the global goal of fighting climate change. However, this trade-off may not exist in situations where those without access to electricity instead rely on energy biomass such as Kerosene, which are particularly detrimental to the global climate. Besides the negative effects on climate, these fuels are also very expensive for the users and harmful to their health (Sustainable Energy for All, 2017; World Health Organization, 2016).

In recent years, prices for solar panels and batteries have decreased dramatically, making off-grid solar a potential cost-effective solution to provide low-income households with cheap and clean energy. In particular, small solar lights to replace kerosene-fueled lighting sources have the potential to reduce emissions, health risks, and household energy expenditures at very low cost. While these new technologies are very promising, there remain many open questions as to their effectiveness in practice. The paper sheds light on three issues: 1) The effect of subsidies and of reduced transaction and information costs on demand for solar lights. 2) The environmental benefits of solar lights through reduced kerosene use and emissions. 3) The private benefits of solar lights in terms of energy expenditure, health outcomes, and school performance.

Experiences from other contexts show that engineering projections may overestimate efficiency gains from novel technologies and that benefits in a real-world setting might be much more limited (e.g. Allcott and Greenstone, 2012; Davis et al., 2014; Fowlie et al., 2018).[1]

This study analyzes both the demand for and impacts of access to solar lights through a randomized field experiment among over 1,400 households in rural Kenya, where kerosene was the predominant energy source for lighting. The school-based intervention that we evaluate consists of five treatment arms in which solar lights are offered to randomly selected

[1]Field experiments on the use of cookstoves in India, Uganda and Senegal have shown that lab tests may overestimate their effects on health and environmental outcomes, with take-up depending on factors such as ease of use and maintenance requirements (e.g. Hanna et al., 2016; Beltramo et al., 2019; Bensch and Peters, 2015, 2019).

households at different price points: market price (USD 9), low subsidy (USD 7), high subsidy (USD 4), and free. A sub-treatment within the free group consisted of a different, more powerful type of light. This design allows us to measure the determinants of take-up as well as subsequent usage and impacts of the lights. We analyze these effects by combining survey evidence with electronic sensor data on usage, and administrative data on educational outcomes.

We find that access to solar lights has large effects on emissions, and take-up responds strongly to the price of the lights with a remarkably linear demand curve, making distribution of free solar lights in such areas a highly cost-effective intervention for CO_2 reductions. While every household that was offered a light for free took one, take-up falls to 70% at a price of USD 4, and to 40% and 31% respectively at USD 7 and at the market price of USD 9. The fact that there was take-up at market price shows that information and transaction costs play a role, as, on the market, lights had to be bought at stores that were often further away from participants' homes. This effect is persistent. Five months later, those offered a light at market price were still 22 percentage points more likely to own a working solar light than households in the control group.

In terms of environmental impacts, access to a solar light reduces kerosene use and associated emissions substantially. Owning a functioning solar light replaced the use of one out of two kerosene fueled lamps per household on average. Owning a functioning solar light reduces a household's monthly emissions of black carbon (BC)[2] and CO_2 by 82.4 grams and 3 kilograms respectively. Taking into account both direct CO_2 emissions and the warming effect of BC, this reduction corresponds to 71.8 kg of CO_2-equivalents[3] averted per month. Furthermore, devices that are fueled by kerosene can emit high amounts of fine particulate matter, owning a solar light reduces particulate matter by 85.7 g of $PM_{2.5}$ in a month. These are very large reductions in percentage terms: 50.1% each for BC, CO_2 , and $PM_{2.5}$ emissions. If all households in Kenya that use kerosene as their main source of lighting—9.3% according

[2] "Black carbon exists as particles in the atmosphere and is a major component of soot. BC is not a greenhouse gas. Instead it warms the atmosphere by intercepting sunlight and absorbing it. [...] BC particles have a strong warming effect in the atmosphere, darken snow when it is deposited, and influence cloud formation. In addition to having an impact on climate, anthropogenic particles are also known to have a negative impact on human health." Zhongming et al. (2011)

[3] A carbon dioxide equivalent or CO_2-equivalent, abbreviated as CO_2-eq is a measure used to compare the emissions from different greenhouse gases on the basis of their global-warming potential, by converting amounts of other gases to the equivalent amount of carbon dioxide with the same global warming potential (European Environment Agency, 2001).

to Kenya National Bureau of Statistics (2021)—received a basic solar light and experienced a similar reduction in kerosene consumption, this would translate into a reduction of 2.1 mega tonnes of CO_2-equivalent per year. This corresponds to around 2.90% of Kenya's total greenhouse gas emissions and 11.60% of Kenya's energy emissions in 2019.

In terms of private benefits, the solar lights lead to a significant reduction in monthly household energy expenditure of USD 2.44, or 59%. However, subsidies may be needed for the net present value (NPV) to be positive in the case of the larger light. In addition to the financial savings, we find beneficial health effects, both with regards to eyes-related and respiratory symptoms. Using standardized questions from The European Community Respiratory Health Survey II, we observe a significant reduction in eye-related symptoms of about 0.23 and 0.25 standard deviations for students and their guardians respectively. Respiratory symptoms improve as well. With regards to schooling, access to solar lights increases students' self-reported homework completion and school attendance, but also reduces their sleeping hours. We do not find an effect on test scores.

The results from this study add to the literature in several dimensions. First, we systematically study the impact of price discounts, information and reduced transaction costs on demand and, particularly, differential usage of solar lights. Regarding the distribution mechanism, our study is similar to Aevarsdottir et al. (2017), who randomly allocate subsidies for the purchase of solar lights through the school to a subset of 2,067 households in rural Tanzania. In their study, subsidies were given at 0%, 25%, 50% and 100% of the market price. The impact of subsidies and reduced information and transaction costs is also investigated in Grimm et al. (2020) and Mekonnen et al. (2021), who both find that although households are willing to allocate a significant share of their budget to electricity, their willingness-to-pay for a solar light remains below the market price. Our results contrast the findings from other studies on preventive health products, which observe that take-up drops strongly when moving from a free offer to even a small fee (Kremer and Miguel, 2007; Ashraf et al., 2010; Cohen and Dupas, 2010; Kremer et al., 2011). Similarly, Berkouwer and Dean (2020) and Fowlie and Meeks (2021) find steep drops in the demand for improved cookstoves and energy-efficient light bulbs, respectively.

Second, to the best of our knowledge, we are the first to provide experimental evidence evaluating the climate-related impact of solar lights in terms of emissions reduction and cost effectiveness of solar lights. Grimm et al. (2017) show that solar lights reduced consumption of kerosene and dry-cell batteries. Additionally, Wagner et al. (2021) found that the replacement of a kerosene lamp by a Solar Home System kit is associated with a reduction of about 36.8 kg CO_2-eq annually. However, in our paper we go one step further and include black carbon in our calculations to get a more accurate estimate for the climate-related impact of solar lights. Although BC is the third-most important driver of climate change after carbon dioxide and methane, it has often been neglected in the literature on energy-efficient appliances (Nichols et al., 2009; Lam et al., 2012b). Wallach et al. (2022) recently found that a solar lighting intervention on fuel-based lighting use and exposure to air pollution led to a significant reduction in exposure to $PM_{2.5}$ and black carbon, as well as substantial displacement of kerosene lamps. In contrast to this study, we go beyond the direct climate-related impact and also consider additional individual benefits.

Third, we developed sensor technology to confirm survey results with actual usage data of the solar lights to avoid the inaccuracy of self-reported usage data, as evidenced by Ramanathan et al. (2017) in a study on clean cooking stoves.

Fourth, we add on several aspects to the literature on individual benefits of solar lights. In terms on impact on educational outcomes, there is a widespread belief among practitioners in the solar field that solar lights can help improve children's school outcomes (Esper et al., 2013). The idea is that better quality lighting and additional lighting time will allow children to study more and under better conditions at home. However, the evidence so far is mixed. Our results are consistent with previous studies which found no effects of access to solar light on test scores at the individual level (Furukawa, 2014; Kudo et al., 2019a; Sharma et al., 2019; Stojanovski et al., 2020)[4]. Hassan and Lucchino (2016), in contrast, observe an increase in math grades for students randomly selected to receive a free solar light. They argue that this is likely driven by an increase in co-studying of students at the school after sunset.

The literature on health outcomes of owing and using solar lights provides mixed results. Aevarsdottir et al. (2017), find an improvement in respiratory health among households that did not own a solar light prior to their intervention. Kudo et al. (2019b) observe a reduction of eye related problems of 10-14 percentage points, but no significant impact for respiratory symptoms. Furukawa (2017) reports a reduction of 0.25 standard deviations for a broad

[4]Furukawa (2014) found that solar lamps lowered test scores but these estimates weren't statistically significant.

index of symptoms related to air quality. Both of the latter studies only consider children's health outcomes. Our study adds by showing that the eye-related symptoms improve not only for children but also for their guardians. In contrast, Grimm et al. (2017) find no statistically significant effect on health indicators for students or guardians. More broadly, in the literature on improved cookstoves, many randomized studies find no significant or lasting impact on health outcomes (Hanna et al., 2016; Calzada and Sanz, 2018). Two exceptions identify comparatively large effects: Bensch and Peters (2015) estimate a reduction of 6–7 percentage points in the prevalence of respiratory and eye diseases, compared to an incidence rate of 10–12% in the control group. Berkouwer and Dean (2020) find an improvement of 0.53 standard deviations in a general health index. However, the estimates from both studies only apply to the primary cookstove user and do not extend to other members of the household. Additionally, there is consistent evidence that shows that exposure to $PM_{2.5}$ increases the risk of aggravating asthma episodes, and respiratory infections.[5] In the long term, authors have identified an increase in respiratory and cardiovascular mortality (including lung cancer). In fact, Mehta et al. (2013) found that each 10 $\mu g/m^3$ increase in long-term ambient $PM_{2.5}$ concentrations is associated with a 12% increased risk of acute lower respiratory infections incidence. Furthermore, Kumar and Foster (2007) found that one standard deviation increase in current $PM_{2.5}$ results in a 0.28 standard deviation reduction in lung function.

Lastly, we add to the literature that shows that using solar lights reduces households' energy expenditure in addition to reducing total household expenditure by a small amount (Grimm et al., 2017; Aklin et al., 2017; Kudo et al., 2019a; Aevarsdottir et al., 2017; Mahajan et al., 2020).

The remainder of the paper is organized as follows. Section 2 describes the context, intervention, data, and estimation strategy of our study. Section 3 presents results. We conclude with a discussion of our results in Section 4.

[5] See Lam et al. (2012a); Miller and Xu (2018); Rajak and Chattopadhyay (2020); Ortega et al. (2021)

2 Background and Study Design

2.1 Context

Global Trends of Light Usage and Policy Environment

Increasing electricity access globally constitutes one of the main goals of this century (e.g. under Sustainable Development Goal 7), and accordingly much effort has been dedicated to achieving this. The expected benefits go beyond the obvious; a recent study from Uganda found positive causal impacts of increased village-level electricity access on livelihood, specifically increasing asset wealth (Ratledge et al., 2022). However, in rural and remote areas where low electricity access is still prevalent, expanding the access to the electric grid tends to be very costly, especially so in Africa (Bos et al., 2018; Golumbeanu and Barnes, 2016).

Thus, off-grid energy systems have been increasingly examined as possible alternatives, and increased in use significantly (IRENA, 2022), largely with much success. Renewable-based off-grid alternatives have been proven to be a viable option for rural electrification (Barnes, 2011; Rahman et al., 2013a; Hansen and Xydis, 2020) and have additionally been shown to be rather cost-effective (Come Zebra et al., 2021; Rahman et al., 2013b).

Solar lights represent one example for these off-grid energy systems. The International Renewable Energy Agency (IRENA) estimates that between 2010 and 2018, the number of people worldwide who used basic solar lights grew from around one to 130 million (IRENA, 2020). Pre-pandemic, prices of solar lanterns had been declining substantially, as costs declined thanks to increased competition, innovation, and efficiency (Lighting Global et al., 2016, 2018, 2020). However, the decreasing price trend has been reversed and affordability of solar lights generally impeded by the COVID-19 pandemic as well as Russia's invasion of Ukraine, causing supply chain disruptions and product component shortages (Lighting Global/ESMAP et al., 2022a,b). Compared to 2020, median prices increased 5-8% in 2022 for medium- and small-sized solar lights respectively. Besides supply chain disruptions related to the COVID-19 pandemic, increased inflation may also have contributed to this price increase (Lighting Global/ESMAP et al., 2022b).

In general, off-grid renewables have attracted both public and private funding over the past years, with approximately USD 200 million focused on solar lights (IEA et al., 2021). Though the off-grid solar market faced substantial challenges from the COVID-19 pandemic, in the second half of 2020 the global sales of off-grid solar lighting increased again by 19%

compared to the first half of the year (IEA et al., 2022). In 2021, investments in the global off-grid solar sector grew by 44% reaching a record USD 450 million (GOGLA, 2022).

In terms of use, grid-access does not seem to be negatively correlated to solar home system (SHS) use (Lay et al., 2013). An analysis of East-Asia has shown that, compared to grid-connected households, households with microgrids or SHSs consume moderately to significantly less kerosene (World Resources Institute, 2016). This might be due to the unreliability of the grid. To cope with these issues caused by the unreliability of the grid and electricity supply, Kerosene consumption tends to substantially increase again over the years by 22.3% on average despite grid-connection, though still only to about half as much as those without any electricity access (Dominguez et al., 2021). Meanwhile, a study of solar systems in sub-Saharan Africa indicates that as solar and battery costs decline, there's potential for decentralized solar systems to be a realistic alternative to grid access regarding the provision of high reliability electricity at competitive cost across many regions of sub-Saharan Africa (Lee and Callaway, 2018). For example, Lighting Global/ESMAP et al. (2022b) estimate that an entry-level SHS with a median price of 213.59$ may be affordable to 30% of the population in Africa and South Asia under a Pay-As-You-Go (PAYGo) financing scheme.

However, even with flexible financing schemes, certain parts of the population remain unlikely to be able to buy a solar system. Our analysis of the demand curve for solar lights provides evidence for the level of price sensitivity that underpins this argument. Similarly, Lighting Global/ESMAP et al. (2022b) estimate that affordability decreases from 30% of the population for an entry-level SHS to 0% (45% "at stretch") for a basic SHS with a median price of 508.13$. In these situations, cheaper small solar lights can be an alternative intervention within reach for poorer, rural households. In addition, other energy schemes, including large-scale grid-expansions, the installation of microgrids (Lee et al., 2016), and even small-scale measures targeted at cookstoves (e.g. Beltramo et al., 2019), have been shown to have a low take-up and unsustained usage effects. Meanwhile, we find a very high take-up of lower-priced solar lights and confirm through sensor data that usage is sustained over a long time span.

Light Usage in Kenya and Policy Environment

Between 2000 and 2020 several initiatives and agencies have been established by the Kenyan government with support from international development partners, with the aim of increasing electrification, such as the 2006 Energy Act along with the Rural Electrification Authority (REA) in 2006, or the Kenya National Electrification Strategy (KNES) in 2018 (Alupo, GA, 2018; Dominguez et al., 2021; Osiolo et al., 2017; Tesfamichael et al., 2020). These programs included, among other initiatives, subsidies for both capital cost of grid extension and connection fees for rural households as well as restructuring of the energy sector (Osiolo et al., 2017). In combination, these programs were very successful: the electricity access rate from both grid and off-grid options reaching 75% in 2018, compared to only 32% in 2014 (Alupo, GA, 2018). Though there is still a vast gap between urban and rural electricity access and consumption, the access to electricity in rural regions of Kenya has also risen from 29% in 2015 to 62.7% in 2020 (World Bank Data, 2021; Alupo, GA, 2018). The public subsidies played a key role in working towards achieving universal access in Kenya (Osiolo et al., 2017).

However, several constraints to achieving universal electrification in Kenya have been identified, one of which is high system costs (Osiolo et al., 2017). Factors that partly determine the adoption of grid-electricity include proximity to installed transformers in public facilities, electricity prices, income, high poverty rates, and energy technology (Dominguez et al., 2021; Osiolo et al., 2017; Tesfamichael et al., 2020). Furthermore, experimental evidence indicates that there is a negative relationship between price and demand for electric grid connections (Lee et al., 2020). Moreover, the Kenyan electric grid is plagued by frequent issues, including black-outs, breakdowns, voltage drops and accompanying long restoration times (Moner-Girona et al., 2019). Comparable to global trends, evaluations in Kenya provide further evidence to the benefits of renewable off-grid technologies like solar, wind, hydro, or hybrid in providing access to electricity cost-effectively in rural areas (Moner-Girona et al., 2019; Zeyringer et al., 2015).

The government of Kenya has stated its intent to eliminate kerosene for household energy consumption (Government of Kenya, 2012, 2015b). In response to the Paris Agreement, the government announced plans to reduce CO_2 emissions by 30% compared to a “business as usual” scenario by 2030 (Government of Kenya, 2015a). While some attempts have been made in this direction, efforts so far have been generally deemed lacking, especially in 2022 after removal of the petrol subsidy while merely reducing the diesel and kerosene subsidies (rfi, 2022; Clean Cooking Alliance, 2022). This policy change by the Kenyan government is not only economically criticized, but also because of its environmental consequences, incentivizing adulteration, and the use of dirty fuels (Institute of Economic Affairs Kenya, 2022; University of Liverpool News, 2022; Shupler et al., 2022).

In 2016, around the time of our study, about 35% of Kenya's population relied mostly on kerosene for lighting (KIHBS, 2018). Around 41% powered their light mainly through the electric grid, 14% used solar lights, and 9% alternative sources such as fire, wood and batteries. As of 2020, 9% of Kenyans still mostly use kerosene for lighting (Kenya National Bureau of Statistics, 2021). Our study population has even less access to the electric grid than the overall population in Kenya, and as a result, 93% of the study participants used kerosene as the main source for lighting prior to the intervention.

Different types of kerosene lamps have different quantities of emissions. The most common are tin lamps and kerosene lanterns (pictured in Figure K.1), with the former causing substantially higher emissions per liter of kerosene than the latter. In our control and free treatment groups, at baseline, 63% of households 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 time of our study, 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 their own village, while 69% saw it at the closest market center and 24% only in a larger city. Meanwhile, awareness of solar lights and other solar systems has risen strongly over the past years, with Kenya having become the most important market in East Africa (Lighting Global/ESMAP et al., 2022b). A World Bank report from 2022 posits that as much as 71% of the Kenyan population are primary solar users (Lighting Global/ESMAP et al., 2022b). Nevertheless, awareness gaps remain especially with regard to the benefits of solar, which may partially explain a stagnation in new sales in recent times (Wagner et al., 2021; Lighting Global/ESMAP et al., 2022b)

Environmental and Health Impacts of Kerosene Emissions

Kerosene-fueled lamps emit carbon dioxide (CO_2), particulate matter 2.5 ($PM_{2.5}$) and black carbon (BC). $PM_{2.5}$ are inhalable fine particles with a diameter of 2.5 micrometers or less that are air pollutant and particularly detrimental to health. BC is a component of $PM_{2.5}$ which primarily forms during combustion of carbon fuels and has an unique set of physical properties. After CO_2, BC is estimated to be the second most important agent contributing to global warming (Bond et al., 2013). At least 88% of the $PM_{2.5}$ mass that kerosene lamps emit corresponds to BC (Lam et al., 2012b).

Kerosene-fueled lighting also has adverse health effects through indoor air pollution, especially of $PM_{2.5}$. There is a broad consensus that indoor air pollution is the most important environmental health risk factor worldwide (World Health Organization, 2016). While much of the indoor air pollution stems from cooking, the role of lighting is less clear.[6]

Educational Impacts of Solar Light Usage

Different studies have explored the role of solar lights in educational performance. Several authors emphasize that study time after school improves the understanding of the contents taught at school. In this sense, the lack of a proper light reduces the opportunities to study at nighttime, which could potentially make the learning process more challenging, and which in turn would affect the student's performance (Kudo et al., 2019a; Dufur et al., 2013; Alstone, 2010; Dang, 2007; Cooper et al., 2006).

Studies that explore this hypothesis report similar results to our findings: Furukawa (2014), Kudo et al. (2019a) and Hassan and Lucchino (2016) found an increase in study hours but only the latter found an impact on math scores while Stojanovski et al. (2020) found no impact at all. Furthermore, the design of our study allows us to rule out potential explanations that other authors have posed as potential reasons that explain the lack of effect. Furukawa (2014) mentioned that the lack of proper charging and the flickering of lights may explain the null statistical significance impact on test scores despite finding an increase in the study time. In our study, at endline, only around 19% of the guardians that own a solar light reported having trouble charging the device, or having a flickering light and/or find the light to be too weak. These authors also mention the possibility of a decrease in sleep time which may impair rather than enhance children's learning process. We report the latter outcome in Table 8 Column 5. We can furthermore generally rule out reporting bias, also proposed by Furukawa (2014), based on our sensor data, which on average align with the self-reported survey data. Both Furukawa (2014) and Kudo et al. (2019a) discuss students not being able to use the solar lights for homework due to other household members

[6] According to World Health Organization (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".

using it, which may possibly also pose an impediment in our case. Like Kudo et al. (2019a) we can also rule out spillover effects to be causing the lack of educational effect (see section 3.5). For Stojanovski et al. (2020) the widespread use of flashlights and a lack of experimental take-up posed a big issue. In a similar way, Table A.1 shows that owning a working solar light didn't have a significant impact on the use of battery powered lanterns, in contrast take-up is covered in depth in section 2.4. Overall, it's likely that a combination of factors played a role (for discussion of this see section 3.4).

2.2 Intervention

We conducted a randomized field experiment that consisted of distributing solar lights in schools in rural Kenya, in order to investigate both 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 (subcounties Nambale and Teso-South), in partnership with SolarAid, a large distributor of portable solar lights in Kenya.[7]

The sampling frame included the 3,360 households that had at least one child in one of these classes.[8] Out of these, 1,410 students were randomly selected into either of our treatment arms or the control group. The final study sample consists of 1,313 households, as there was about 7% attrition in the follow-up survey a year later (discussed in more detail below).

The treatment consisted of giving a free solar light, or a voucher to purchase a solar light, to guardians (usually a parent or other relative of the child in the study) at the end of the baseline survey. There were five different treatment arms, which vary along two dimensions: price and type of light. The former allows us the 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 (see Figure F.1 for a graphical depiction of the study design).

1. Free basic light (N=200): Guardians received a free solar light. This light provides up to 27 lumens and has a battery life of 8.1 hours at maximum brightness (Lighting Global, 2012). For comparison, a simple kerosene tin lamp provides around 8 lumens

[7]Children 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 leave school before the study ended.

[8]To identify which children belonged to the same households, we visited the schools prior to the intervention. For households with more than one student in grades 5–7, we randomly selected one student to be in the sampling frame.

and a kerosene lantern around 45 lumens (Mills, 2003).

2. Voucher for basic light with high subsidy (N=209): Guardians received a voucher to purchase a basic solar light for USD 4 (compared to the market price of USD 9). Surveyors showed participants the light and read a script containing basic information about the light,[9] before informing them that they could redeem the voucher at the school within 4–6 weeks. The voucher contained the respondent's name and was not transferable.[10]

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 USD 2 subsidy).

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 light for USD 9 (i.e. there was no subsidy). In addition to helping us estimate the price elasticity of demand, this treatment also helps estimate the effect of the reduction in information and transaction costs provided by the intervention, in comparison to the control group, which could purchase a similar light at the same price elsewhere on their own.

5. Free larger light (N=200): This treatment was identical to that of group 1, but the guardian received a larger type of 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 (Lighting Global, 2014). The market price of this light was USD 24.[11]

6. Control group (N=400): This group participated in the surveys in the same way as the treatment groups, but received no opportunity to receive a light through the school.

Randomization

Randomization of treatments was done prior to the baseline surveys, stratified at the school level. We randomly selected 70 students from each school to participate in the study (20 for

[9] See Appendix Section J.

[10] We later conducted audits to ensure that respondents did not sell or trade their vouchers.

[11] The brand name of the basic light was "Sun King Eco", the one of the larger light "Sun King Mobile". Both lights are quality assured by Lighting Global, a World Bank Group initiative. See Appendix Figure K.2 for images.

the control group, and 10 for each of the treatment arms.)[12] Since assignment was stratified at the school levels and not all schools have the same proportion of participants across treatments, we include school fixed effects in all estimations.

2.3 Data

We combine data from baseline and endline surveys (with both the students and their parents or other guardians) with electronic sensor data from a subsample of the solar lights, and administrative data on student test scores. Baseline surveys took place in June–July 2015 and endline surveys in February–March 2016[13].

Baseline surveys. First, baseline surveys were conducted among the students directly in the school. The student baseline survey includes information about the students' school attendance, school- and homework, ownership and usage of lighting sources, including solar lamps, time use, and health symptoms.

As part of the survey, students were asked to provide the name and phone number of the guardian primarily responsible for them (i.e. a parent or other primary caregiver). They then received a paper slip inviting the guardian to come to the school for their baseline interview, which took place several days later.[14] Most commonly, the guardian was the mother (50.6%) or father (28.9%). In other cases, it was a grandmother (7.8%), aunt (3.8%), grandfather (2.8%), or uncle (2.5%).[15]

The guardian baseline survey includes information about key characteristics, such as household size, performance of agricultural activities, connection to the grid, ownership and usage of lighting sources, including solar lamps, ownership of other assets, consumption and expenditure. The lights were distributed at the end of the guardians' baseline survey.

Endline surveys. The endline surveys were administered at the school for students and

[12] Two schools had less than 70 eligible students. In these schools, we allocated fewer students to the voucher treatments, and correspondingly increased the number of students in voucher treatments in the other schools, to keep the total number of participants similar across all treatments (see Appendix F for details).

[13] See Appendix Figure F.2 for a full timeline.

[14] Travel costs for guardians to the school were reimbursed. Over 90% of guardians came to the school for their baseline survey. In the remaining cases, surveyors followed up at home to conduct the survey there. The share of guardian surveys that took place at the school vs. at home is balanced across treatment arms.

[15] To be included in the survey, guardians had to live at least four nights a week at the same place as the student. If it turned out at the interview that a guardian did not meet this requirement, we asked another guardian of the student to participate.

at home for guardians.[16] The endline survey for students included questions on time use, on lighting as well as on education and health-related outcomes. The endline survey for guardians also included questions on time use, lighting and health, and in addition questions about energy sources, household expenditures, and psychological outcomes.

Sensor Data. 220 of the solar lights that were distributed throughout the intervention were equipped with a sensor that recorded when a solar light was being used. Households were not informed about the sensor when they received the solar lights, but only learned about it a few weeks after the baseline survey. The installation and functioning of the sensors is discussed in detail in Rom et al. (2020).

Piloting and qualitative data collection. Prior to the intervention, we also conducted semi-structured interviews and focus groups gain more information about the context and strengthen the study design and survey instrument. 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.

Administrative test data.

We collected test scores from end-of-term exams in school 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.

Attrition

Despite our efforts to mitigate attrition by following up with participants at their homes, we were not able to locate all guardians and students for the endline survey. The endline survey is crucial for us to measure the impact of access to a solar light, since this survey contains the first stage outcome variable: whether the household owns a functioning solar light. The attrition rate for guardians is 7%, and our final study sample therefore includes the $1,313$ households with guardian follow-up surveys. In addition, there were 8% of households

[16] If the student was not present on the interview day, surveyors tried to reach them at the school another day or interview them at their home.

for which the guardian took part in the endline survey, but the student did not. Impact estimates for student outcomes therefore have a somewhat smaller sample size.

Attrition rates are slightly unbalanced for both students and guardians between the control group and all treatment groups combined (8% in the guardian control group, 6% in the guardian treatment group, difference statistically significant at the 10% level; and 15% in the student control group, 14% in the student treatment group, difference not statistically significant).

Attritors and non-attritors have somewhat different characteristics. For guardians, attrition is higher when the guardian is not a parent of the student.[17] Among students, attritors are more likely to be female, older or students with lower grades at baseline (potentially due to higher school dropout rates in these groups). Moreover, students whose guardian is a grandparent or not the parent are more likely to drop out of the study

In most of the outcomes, the sign of the point estimate of the difference is the opposite for students and guardians. There are some subtreatments for which the difference is statistically significant.

Below we provide robustness analyses using Lee bounds (see Appendix Table C.3) and inverse probability weighting to account for imbalances in attrition. Results are highly robust to these adjustments.

We address potential bias from attrition in two ways. First, we use the approach developed by Lee (2009), which provides lower and upper bounds for treatment effects by making extreme assumptions about the outcomes of attritors. Second, we apply inverse probability weighting to rebalance the observable sample characteristics between treatment and control groups (Wooldridge, 2002, 2007). This approach gives more weight to participants with characteristics that are underrepresented in the endline survey. See Section 3.5 for details.

Balance Tests and Summary Statistics

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

[17] This is likely to be the case because where the guardian is not a parent, it is more likely that the primary caregiver of the student will have changed since the baseline survey.

comparing all treatments combined to the control group. All regressions include school fixed effects. The F-test for joint significance is estimated using stacked regressions, to allow testing across all regressions.

Balance of randomization. The F-test of joint significance of all baseline outcomes compared to the control group has a p-value of 0.73 when pooling all treatments and 0.25 when analyzing each treatment group separately.[18] For individual treatment arms, the p-values vary from 0.25 to 0.99. Not surprisingly, 6 out of 90 coefficients are statistically significantly different in the comparison to the control group. All five of these differences refer to the gender of either the student or the guardian. Even though these differences are not statistically significant when pooling all treatment arms together, we include respondent gender fixed effects in all of the following impact estimates.[19]

Descriptive statistics. Only 1.3% have a connection to the electric grid, and the share of households who already own a solar lamp at baseline is 5.3%. 37% of students were in grade 5, 36% in grade 6 and 27% in grade 7. Around 57% of students and 64% of guardians are female. Students are on average $1,312$ years old, and about 14% from the final sample of students are from the replacement list[20]. Most of the guardian's interviews (95%) took place at the school. In 78% of cases the guardian is the student's parent, for 11% it is a grandparent. Participants live in households with close to seven people on average. Over 99% of households conduct agricultural activities.

2.4 Identification Strategy

Our empirical strategy proceeds in three steps. First, we analyze take-up by treatment arm. Then, we compare light usage across treatments conditional on take-up. Lastly, we estimate the treatment-on-the-treated (TOT) effect of owning a working solar light on various environmental and household outcomes.

Take-Up

We analyze two measures of take-up: the share of participants who received or bought a solar light through our program, and the share that owned a working solar light at the time

[18] Following Lee and Lemieux (2010) and Pei et al. (2019), we use stacked regressions, which allow for joint hypothesis testing across regressions.

[19] For robustness, we also show estimates without gender fixed effects in Appendix E.

[20] If a student was not present for the interview, the next available student from the replacement list was interviewed instead.

of the endline survey. We estimate take-up with a simple linear probability model, regressing a dummy variable equal to 1 for those who took or own a light on treatment dummies. The two take-up measures can differ because some households owned solar lights prior to the intervention, some purchased other solar lights on the market during the study period, and some lights from our program (10.6%) broke before the follow-up survey.

Usage

Conditional on take-up, usage of solar lights might differ across treatment groups. Usage might vary with price of the light because of selection effects (e.g., households who 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). In addition, usage might be different in households that receive the larger light compared to those who receive the basic light.

To analyze whether this is the case, we investigate the local average treatment effect (LATE) on solar light use for each treatment arm separately in five separate regressions. The sample for each regression consists of households in the control group and the respective treatment group k. For each k, we then estimate the following IV regressions

$$\begin{aligned} solar\_works_i &= \pi_k T_{ik} + \zeta_i + \gamma_j + u_i && (1) \\ y_i &= \beta_k \ \widehat{solar\_works}_i + \xi_i + \mu_j + e_i && (2) \end{aligned}$$

where T_{ik} is a dummy for assignment of household i to treatment group k and $solar\_works_i$ is a dummy indicating whether household i owns a working solar light at the time of the follow-up survey, ζ_i and ξ_i represent respondent gender, γ_j and μ_j school fixed effects, and u_i and e_i are error terms. Under standard IV assumptions, β_k represents the LATE of owning a working solar light on outcome y for compliers in treatment group k, i.e., on households who own a working solar light at the time of the follow-up survey as a result of the treatment k.

We then test for heterogeneity in usage across treatment arms (i.e., we test H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$). Since these β-coefficients are obtained from separate regressions, we estimate these simultaneously in a stacked regression. This yields a joint variance-covariance matrix across the five Two Stage Least Squares (TSLS) estimations which enables us to conduct the desired hypothesis test.[21]

[21] The β_k-coefficients and their standard errors are the same as when estimating Equations (1) and (2) for each k separately.

To preview the corresponding findings, usage does not vary across treatment groups. For this reason, we estimate the pooled effects of owning a functioning solar light for most of the impact analysis, as follows.

Impacts of Solar Lights

We estimate the TOT effects of owning a functioning solar light on environmental impacts and household outcomes as follows: Since take-up varies by treatment, the first stage will be different for each treatment group, so each treatment will be included as a separate instrument for owning a functioning solar light. In the second stage, we combine all treatments, which gives us an estimate of the pooled LATE of having a working solar light. Specifically, we estimate the following equations using TSLS:

$$\begin{aligned} solar\_works_i &= \pi_1 T_{i1} + \pi_2 T_{i2} + \pi_3 T_{i3} + \pi_4 T_{i4} + \pi_5 T_{i5} + \zeta_i + \gamma_j + u_i && (3) \\ y_i &= \beta\ \widehat{solar\_works}_i + \xi_i + \mu_j + e_i && (4) \end{aligned}$$

For some of the analysis, we are interested in the differential treatment effects by type of light. In these cases, we estimate Equations (3) and (4) separately for each type of light (in samples including participants in the control group and in the treatment arms for the respective type of light) and again use stacked regressions to test for heterogeneity.

Comparison Mean

To benchmark the magnitude of the estimates, we calculate the "control complier mean" (CCM). The CCM is the average outcome of those households in the control group who 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 TOT estimate. This approach was originally proposed by (Katz et al., 2001). 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).[22]

Robustness Checks

We present a number of robustness checks in Sections 3.5, including accounting for attrition, testing for spillovers and type II errors, and controlling for additional baseline characteristics.

[22] We do not calculate the CCM for outcomes which are standardized based on their distribution in the control group (i.e. health outcomes) since it is uninformative.

3 Results

This section first presents take-up and usage to investigate how price and reduced transaction and information costs affect demand for and usage of solar lights. We then investigate the environmental impacts in terms of kerosene consumption and emissions. Finally, we analyze the private benefits to the households in terms of energy expenditure, health, and educational outcomes. Section 3.5 provides robustness checks.

3.1 Price Elasticity of Demand

Demand for solar lights responds strongly to price. The red line in Figure 1 shows the share of households in each treatment group who took a light through the study. By construction, this share is zero for the control group who was not offered a light. All participants who were offered a free light took it. For vouchers with a co-pay of USD 4, take-up drops to 69.5%. At USD 7 it drops to 39.9% and at the market price of USD 9 to 30.6%. Based on this exogenous price variation we can calculate the price semi-elasticity of demand. It is 0.5, that is, for a 1% increases in price, take-up drops by 0.5 percentage points. The corresponding demand curve is remarkably linear.

The green line in Figure 1 shows the share of households that owned a working basic solar light at the time of the endline survey (i.e. seven months after our intervention). This includes both lights obtained through our intervention and those purchased in some other way. By this time, 18.3% of participants in the control group also have a working solar light. Nevertheless, there is still a strong impact on ownership. The strong gradient with respect to price shows that subsidies can be effective in stimulating the use of solar lights. Even those offered a light at the market price of USD 9 still have a 22% percentage point higher ownership share than the control group, indicating that providing information about the solar light and reducing transaction costs compared to purchasing a light in the market can substantially increase take-up.

Take-up rates could be influenced by the cash availability to purchase the product. In an RCT in Kenya by Dupas (2008), demand for bednets fell less steeply with price when households were given more time to raise the money to purchase them.

Households in this experiment had up to three months to redeem their voucher which allowed them to save to purchase it. The time taken to redeem the voucher increased with the price of the net: from 3 days on average in the free net group to 35 days in the 70–90 KES price group, and to 54 days in the highest price group. This adoption could be considered a case of relative "slow adoption" in comparison to other studies such as Jensen's paper (2007). This study analyses the economic effects of "fast adoption" of mobile phones in Kerala, India on the local fish markets. In this study, phones were bought primarily by the largest boats, since they faced the largest potential gains to arbitrage and were also more likely to be able to afford cellphones, which were initially expensive. However, the smaller fishermen still obtained spillover benefits from improved market efficiency even though they did not use the phone directly.

In the context of our experiment, vouchers could be redeemed within 4 to 6 weeks after the baseline interview. Guardians that received a voucher were given specific dates upon which they could come back to the school to purchase the lamp. Field officers waited outside the school. Unlike previous studies, the time taken to redeem the voucher didn't increase with the price: from 21 days on average in the high subsidy group to 20 days on average for the lower subsidy group and to 24 days in the market price group.
The relatively homogeneous pace of adoption across voucher groups could be influenced by the presence of spillovers among neighbors. This is known in the literature as learning/imitation effect. The neighbors and/or classmates of the guardians and students that received the solar lights for free or redeemed their voucher, learn from, and imitate the treated individuals, and their change in behavior can lead to them redeem a solar light. In fact, among the guardians that received a voucher and redeemed it, 94% of the guardians reported knowing a neighbor that owns a solar light, and about 53% of these guardians talked with their neighbors about solar lighting (89% and 30% respectively in the case of guardians that received a voucher but didn't redeem it).
Note: there is a bar graph that shows the voucher redemption by dates that may be helpful.

3.2 Usage

Do Subsidies Affect Usage?

Conditional on owning a working solar light, usage might be different for different treatment groups, because of both potential selection and treatment effects. Households that decide to purchase a light may differ from those who only take one when it is offered for free (e.g. in terms of higher need for lighting) and the act of paying for a light could make households more likely to use it. Similarly, recipients of a large solar light might potentially use the light more. Whether this is the case will inform our empirical strategy when estimating the impact of the solar light on household outcomes.

Table 2 shows usage of the solar light on the day and the week preceding the endline survey. For guardians, the corresponding F-test shows no significant heterogeneity and no correlation between the price of the light and usage, both when including and excluding the larger light in the test. For students we do find evidence of different use, and we reject at the 10% confidence level that students use light from all treatment arms the same amount, both in terms of hours per day and days per week. When estimating the impact of solar lights in what follows, we will therefore pool the different treatment arms in the second stage of the TOT analysis, as discussed in the empirical strategy section.

Thanks to sensors installed on the solar lights we know that solar light usage remains constant over time, at least during the study period, as first reported by Rom et al. (2020). Figure 2 depicts this finding: conditional on usage (i.e. the sensor activating for at least 1 minute in a given week) the average number of days per week as well as average hours per day remain remarkably constant throughout the study period (August 17$^{\text{th}}$, 2015 − March 20$^{\text{th}}$, 2016). This allows us to compute the impact of the solar lights on emissions for the entire time period of the study and beyond in a straightforward way, as we do later on, by assuming that usage does not drop off over time. It is important to note the difference between the conditional and unconditional curves. The reason for such discrepancy lies in multiple factors. First of all, when looking at sensor data we cannot differentiate between voluntary and involuntary (i.e. due to breakage) non-usage of the lamp. Apart from people who stop using the light, the unconditional line also takes into consideration the natural breakage rate of the lights (which we had estimated based on the survey at almost 1% monthly) as well as the breakage rate of the sensors themselves. In particular, it appears to be the case that lights on which sensors were installed tend to break more often than the others. This is reasonable given that sensors were added post-production specifically for the study. One additional insight given by the sensors is that there seems to be no differences between impartial sensor data and self-reported survey data on average, which reassures us about potential issues concerning survey answers such as social desirability bias and others

(Rom et al., 2020). For instance, the average hours per day of usage based on the survey[23] is 3.35 hours for guardians and 2.47 hours for students, whereas based on the sensor is 4.27 hours. From these numbers we can infer that guardians and students might be sharing and thus double-reporting the light for roughly 1.55 hours per day, the difference between their reported usage combined and the sensor-logged usage. Double-counting is not an issue when looking at days of usage per week, by construction. Based on the survey answers, guardians used the lamp, on average, 6.76 days per week, while students used it, on average, 6.57 days per week. This seems to be roughly in line with what sensors tell us: 6.87 days per week. More details on the handling of the sensor data can be found in Appendix H.

Impact on Lighting Use

Table 3 shows the effects of owning a working solar light overall on total light use in the month preceding the endline survey. This is important to assess whether the new solar light fully replaces other lighting sources, or whether there is stacking i.e. whether some of the light from the solar light is used additionally to the pre-existing light sources. While there is no significant effect on lighting use by the guardian, students in households with a working solar light use an average of 24 more minutes of any lighting per day, up from 3 hours and 14 minutes in the control complier mean (a 12% increase). The fact that the additional light use is concentrated on the students could potentially be a result of the distribution of the light through the school.

However, this aggregate impact on light use may mask certain shifts in the light use patterns of the guardians and at the same time supports the stacking hypothesis. When we analyze the light use by types of light the guardians use, we can observe that guardians that own a functioning solar light reduce the number of hours using a tin lamp by approximately 2 hours (down from about 2 hours and a half in the control complier mean), as well as a reduction in the time using a kerosene lantern, and electric power as sources of lighting in the guardian's daily activities (about 92.5%, and 88.4%, respectively, in comparison to the control complier mean). See Appendix Table A.1[24]. Furthermore, the students are more likely to report solar lights as the main source of lighting when they need to do homework, and less likely to rely on tin lamps or kerosene lanterns for this activity. The solar light also

[23] The survey-based averages are Treatment-on-the-treated LATE estimates of having a working solar light on solar light use, i.e., the equivalent of Table 2 but pooling all treatment arms.

[24] We do not have such information on types of lights used for the students

leads to more consistent lighting. Households with a solar light are 38.8 percentage points less likely to have to sit in the dark because they ran out of fuels, battery or other energy sources for lighting devices (down from 47%).[25]

Combined with the information from Table 2 that the solar lights were used for multiple hours a day on average, these results indicate that while most of the time the solar light replaces another light, it does not completely crowd out usage of other lights, i.e., there is some degree of "stacking" of light sources. This is also consistent with what we find below in terms of the number of kerosene lights used. While stacking is a common behavior, an analysis of potential drivers indicated that physical opportunity, including factors such as affordability and functionality, accounts for the broad majority of stacking (Perros et al., 2022).

3.3 Environmental Impacts

Kerosene Consumption and Related Emissions

Table 4 shows that solar lights reduce kerosene use substantially. A functioning solar light reduces the number of kerosene lamps used in the preceding month by 0.90, down from a control complier mean of 2.4. Looking at kerosene-fueled lights by type of light, we find a reduction of 0.9 tin lamps and 0.1 kerosene lanterns used, consistent with the widespread use of tin lamps among households in our sample.[26] This is highly relevant for emissions, since a tin lamp emits about 10 times more black carbon and about 7 times more $PM_{2.5}$ than a kerosene lantern per liter of kerosene used. Households are 29.6 percentage points less likely to have used a kerosene-fueled lamp the previous evening, from a baseline of 95.9% in the complier control group.

As a result of the reduced use of kerosene-fueled lights, households purchased 1.29 fewer liters of kerosene in the month preceding the endline survey, a 50% reduction. Annualized, this corresponds to roughly 15 fewer liters of kerosene purchased per household. We can use this survey evidence on kerosene consumption to convert the reduction in kerosene use to a reduction in emissions based on work of the environmental literature.

Measuring the impact of kerosene fueled lamps on climate change requires two steps:

[25] In addition to more lighting hours, solar lights also increase the quality of light, in particular in comparison with tin lamps see Section 3.3.

[26] As mentioned in section 2.1, over 63% of households used only tin lamps during the preceding month, about 36% used both types, and less than 0.4% used only kerosene lanterns

first, calculating emissions per liter of kerosene burnt by type of light; second, converting the emission components into CO_2-equivalents. For the first step, we draw on information from a study conducted in Kenya's neighboring country Uganda, which measured emissions of CO_2, $PM_{2.5}$, and BC per kilogram of kerosene burnt in tin lamps and kerosene lanterns (Lam et al., 2012b). The authors find that emissions amount to 2,770g of CO_2, 93g of $PM_{2.5}$, and 90g of BC per kilogram of kerosene for tin lamps, and 3,080g of CO_2, 13g of $PM_{2.5}$, and 9g of BC per kilogram of kerosene for kerosene lanterns. About 0.8 kilograms of kerosene correspond to one liter.[27]

The second step requires converting BC into CO_2-equivalents. There are several differences in the impact of CO_2 and BC on climate change. BC acts both fast and locally. It has much stronger effects than CO_2 even though it remains in the atmosphere only for about one week, whereas CO_2 remains in the atmosphere for up to a century (Nichols et al., 2009). Nevertheless, the effects of BC can continue for years and even decades, due to the thermal inertia in the climate system (IPCC et al., 2021). As such, BC's climate impact varies substantially across world regions. BC is the most sensitive to regional differences of all short-lived climate forcers (SLCFs) (Aamaas et al., 2017), which play a key part in achieving the Sustainable Development Goals (Haines et al., 2017; Tibrewal and Venkataraman, 2021). BC's impact depends on its atmospheric abundance and concentration (Bond et al., 2013, 2011), which is highest above major source regions (Bond et al., 2011; Ramanathan and Carmichael, 2008) as well as its residence time in the regional atmosphere. Because of a combination of energy-related burning (this includes kerosene and other fossil fuels) with open burning of biomass (e.g. wood or grasslands through savanna fires), which is more common in Africa than in many other regions, there is a comparatively higher BC concentration in the atmosphere above Africa, as well as South Asia and Latin America (Bond et al., 2013). Drier regions, such as west and central Asia and Africa also experience a longer residence time of BC in the atmosphere (Reddy and Boucher, 2007) and different models suggest that BC has a stronger effect in tropical rather than temperate regions (Bond et al., 2013).

To estimate the intervention's impacts on emissions, we multiply each household's kerosene purchase at endline by emissions per liter corresponding to the type of light the household

[27] Kerosene sold in Kenya must have a density in kg/dm^3 of between 0.771 and 0.830 (TotalEnergies, 2022), so we take the mid-point.

uses (for the 19.4% of households that use both types, we assume that they use half of the kerosene for each type).

Comparing these emissions across treatment arms allows us to estimate the impact of access to a working solar light, as presented in Table 5. A working solar light reduces households' monthly emissions by 82.4g of BC and 3kg of CO_2. In terms of CO_2-equivalents, this corresponds to a reduction of 71.8 kg per month.

Given the uncertainty surrounding the global warming potential equivalence of BC, we calculate lower and upper bounds for the CO_2-eq emissions reduction based on the uncertainty bounds given by Bond et al. (2011). The resulting range goes from of 33.5kg in CO_2-eq up to 110.1kg per month per household. We will take this range into account for the cost-benefit analysis below as well (see Table B.2).

CO_2 Abatement Costs and Cost Effectiveness

Based on these results, we can estimate the abatement cost of reducing CO_2 and BC emissions through the use of solar lights. The calculation is based on the following assumptions: Solar lights have an infinite life-span with a monthly breakage rate of 0.99% per month[28], and 47.2 kg of CO_2 embedded in the light from the production.[29] In our setting, the basic and large solar lights have a market price of USD 9 and USD 24, respectively.[30] We assume that these prices include all administrative and logistics costs that occur when distributing solar lamps at schools. These prices represent the subsidy that would need to be payed per lamp when distributing the solar lamps for free. Since we seek to calculate the abatement cost that would occur if our intervention were to be scaled up, we take into account that

[28] To calculate the breakage rate, we used the information from the guardian's survey on whether any of the solar lights the guardians own still function at the time of the endline. The criteria for inclusion in the breakage rate sample are i. Households that received a free light ii. Households whose solar light does not have a sensor.

[29] This amount is based on estimates from Alstone et al. (2014). While they do not assess the exact same lights as the ones in this study, we use the estimates of the primary energy requirements that are most comparable, which translate to 27.78 kWh. Based on Dones et al. (2004), we use the estimate that approximately 1700g CO_2-equivalents are emitted per kWh of energy used to produce the solar lights. This is a conservative estimate as it assumes that all parts of the lights are produced with coal energy in inefficient power plants in China. See detailed calculations in section G.1.

[30] A World Bank cross-country case study of Africa and South Asia indicates that lamp prices have generally remained at comparable levels to those in our study (Lighting Global/ESMAP et al., 2022b). The study compiled a median price of single lights (comparable to our basic light) of 9.08$ in 2022, with over-the-counter lamp prices ranging from 3.71$ to 39.91$, and a median price of single lights with mobile chargers (comparable to our mobile light) of 27.3$, ranging from 6.14$ to 51.29$. Based on these prices, they estimate that basic and mobile lamps are affordable for 95% and 58% of people in the surveyed countries respectively.

costs and take-up rates differ depending on the type of distribution and amount of subsidy paid. In case of distribution via vouchers, the subsidy would decrease but additional money management and logistics costs could occur. Details on how we account for these differences of fully and partly subsidized distribution can be found in Appendix G.

Given these assumptions and when distributing the basic and mobile solar light for free, the abatement cost amount to USD 1.32 and USD 3.44 per ton of CO_2-equivalents averted, respectively. When subsidizing solar lamps only partly, this cost is even lower, ranging from USD 0.08 when providing vouchers at market price, to USD 0.36 and USD 0.77 when offering vouchers with a low and high subsidy, respectively (Appendix Table B.1).

An important factor when calculating the abatement cost is the type of light used in the absence of the solar light. Compared to the entire country of Kenya, households in our control and free treatment groups, at baseline, are more likely to use kerosene as the main source for lighting (90% at baseline vs. 9% in the country as a whole in 2020 (Kenya National Bureau of Statistics, 2021)) and households that rely on kerosene are more likely to use tin lamps as the main source of lighting opposed to kerosene lanterns (94% compared to 64% for Kenya as a whole). When using national averages instead of averages from the study sample, the cost per ton of CO_2-equivalents is between USD 0.12 and USD 5.12, assuming that solar lights could be targeted perfectly to households who would otherwise use kerosene-fueled lights (Appendix, Table B.1).

Based on our results, a scale-up would be less costly (for the implementing institution) if solar lights were to be distributed via vouchers.[31] However, welfare gains from CO_2 reduction are also smaller, since take-up rates of solar lights decrease with increasing private co-payment. We estimate welfare gains using the social cost of carbon (SCC). In 2020, the U.S. Interagency Working Group calculated that the SCC was USD 76 per tonne of CO_2 (Interagency Working Group on Social Cost of Carbon, 2021). In the European Union's carbon market the current price of a tonne of CO_2 is around 100 (Trading Economics, 2023). However, Rennert et al. (2022) suggest using USD 185 per ton of CO_2, according to newest estimates using improved probabilistic socioeconomic projections, climate models, damage functions, and discounting methods. Multiplying these estimates with the tons of CO_2 reduced through our intervention, leads to a welfare gain of around USD 340 000 - 1 260 000

[31]It has to be noted, that our cost estimate for the scale-up of the intervention using vouchers represents a lower bound. It is likely that higher logistics costs occur in a national scale-up.

for the free basic light, and around USD 104 000 - 386 000 for the market price vouchers. For all types of distribution, the abatement cost estimates from our study compare favorably with the SCC. Yet, the SCC does not take the warming effect of BC into consideration; it is thus only an illustrative comparison.

The abatement cost estimates also compare favorably to many other programs to reduce CO_2 emissions. For example, Baurzhan and Jenkins (2016) estimate a cost of 150–626 USD per ton of CO_2 averted through off-grid solar photovoltaic (PV) systems in Sub-Saharan Africa (SSA), demonstrating that such systems remain unfeasible for the rural poor in SSA. The IEA (2022) meanwhile estimates an average global cost of 32.98 USD per ton of abated CO_2-eq through all types of solar PV. Regarding mini-grids, in a comparison of various solar photovoltaic systems, Breyer et al. (2015) estimated avoided GHG emissions of approximately 380 EUR per ton CO_2-eq for both new built off-grid hybrid photovoltaic–battery–diesel mini-grids in Rwanda as well as for off-grid photovoltaic solar home systems in Sub-Saharan Africa.

There are, however, other interventions that are similarly or more cost effective, such as a program which offered households in Uganda money to conserve trees, for which Jayachandran et al. (2017) estimates that the net present cost per ton of abated CO_2 is less than USD 3 assuming that the effects persist with a permanent program. In a recent study in Kenya, Berkouwer and Dean (2020) reported that investing in a more energy-efficient cook stove reduces greenhouse gas emissions at a cost of USD 5.82 per ton of CO_2-equivalents.

Extrapolating the results of our study, a back-of-the-envelope calculation suggests that if all households in Kenya that use kerosene as the main source of lighting —9.3% according to Kenya National Bureau of Statistics (2021)—had access to one basic solar light and experienced a reduction in kerosene consumption equal to the one found in our study, this would correspond to a reduction of 2.1 mega tonnes of CO_2 per year. This amounts to around 2.90% of Kenya's total greenhouse gas emissions and 11.60% of Kenya's energy emissions in 2014; again, this comparison is indicative, since national greenhouse gas emissions do not consider the warming effect of BC (Appendix, Table B.1).[32]

As a robustness chack, we showcase our cost effectiveness results for a range of Black Carbon conversion factors due to the uncertainty surrounding BC's global warming potential

[32]The assumptions for these calculations are listed in Appendix Table G.1. We are using estimations from World Resources Institute (2017), as well as the latest Kenya Integrated Household Budget Survey from 2015/2016.

in Table B.2 . Estimates vary significantly from USD 0.62 to USD 38.00 depending on the chosen conversion factor.

One limitation of our calculations is that they do not include CO_2 emissions and other environmental damages from disposing of the solar light. To our knowledge, no such assessments are currently available.

3.4 Private Benefits

Energy Expenditures

Table 6 shows total impacts on energy expenditure and its components. The larger light leads to more than twice the reduction in energy expenditures than the basic light (USD 1.14 vs. 2.44 per month, corresponding to a reduction of 28% for the basic light and 59% for the larger light). This difference is not mainly driven by kerosene use.[33] Column (3) shows a large reduction in mobile charging expenses for the larger light: 87 cent per month, down from USD 1.11 for the control complier mean. The feature that enabled the larger light for mobile phone charging therefore seems to make a big difference.

To analyze the private benefits of owning a working solar light, we express the expenditure savings in terms of net present value (NPV). We undertake the analysis separately by type of solar light, given the significant differences in both prices and expenditure reductions between the different types. For the NPV calculations, we assume a monthly interest rate of 7.5% which is based on the cheapest commonly available loan at the time.[34] Additionally, we do not impose a finite life span of the solar lamp but take into account the monthly breakage rate derived from survey responses. To obtain the NPV we subtract the respective market price from the present value of the estimated expenditure savings.[35]

The NPV for the basic light is $5.43 while the large light has a NPV of $6.96. The calculations based on the survey-derived breakage rate imply that buying a basic or large

[33]The variable presented in Table 4 Column (3) *Kerosene purchased (l/month)* is based on a different question than the one reported in Table 6 Column (2) *Kerosene*. In the former, the respondent is asked to report the amount of liters purchased in a month, and in the latter, the respondent is asked to report the amount spent in kerosene, in KES. Thus, any differential effect between these two outcomes could be associated to potential reporting errors.

[34]This was the rate offered by M-Shwari, a widely used mobile banking product for digital loans. According to the Kenyan FinAccess Household Survey 2016, over 95% of rural households that were mobile bank users owned an M-Shwari account (Central Bank of Kenya et al., 2016).

[35]Unlike in the previous subsection when calculating the CO_2 abatement cost, we do not take into account take-up rates, and the cost of the intervention for this analysis. The idea is to calculate private benefits and costs, once a household has decided to purchase a solar light.

light at full price pays off after 11 and 18 months, respectively.

Health

We use standardized questions from the European Community Respiratory Health Survey II and Bates et al. (2013) to understand possible effects on respiratory symptoms, and questions from Lee et al. (2002) to study eye health.[36] Following Bates et al. (2013), we summarize these outcomes in two indexes, ranging from 0–5 for respiratory symptoms and from 1–6 for eye-related symptoms, expressed in standard deviations (based on the distribution of the control group).

Table 7 shows the impact on these two health indexes for students and guardians, respectively. There is a significant reduction in eyes-related symptoms of about 0.23 standard deviations for guardians and 0.25 standard deviations for students. The reduction in respiratory symptoms is similar in magnitude for students, and smaller for guardians. Children experience about one third of a standard deviation reduction in respiratory symptoms. The point estimate for guardians shows a reduction of 0.27 standard deviations. These improvements in health outcomes are consistent with the estimated reduction in $PM_{2.5}$ emissions by 50.1% which we observe in the last column of Table 5.

Education

Access to better lighting may help increase students' learning as it may allow them to spend more time doing homework after dark. We find that indeed, access to a functioning solar light increases homework completion as well as time spent in school. Nevertheless, there is no effect on test scores. Table 8 shows those results. The probability that, in the week prior to the endline survey, students were able to complete homework each day on which it was assigned is 15.6 percentage points higher for those with a solar light compared to the control complier mean of 65.0%. The share of homework done after dark is 11.4 percentage points higher than the control complier mean of 72.3%.[37] The time dedicated to homework and personal studies increases by 19 minutes, up from 2.4 hours. However, this is not statistically significant. On the other hand, sleep hours fall by 0.4 hours compared to 8.4 hours in the

[36] Appendix I lists the specific questions used.

[37] The variables in Columns 1 and 2 are only asked at the 87.4% of the students who reported receiving homework at least once in the week before the endline survey. The probability of this to be the case is balanced across treatment and control group (see Columns (6) and (7) Appendix Table A.9)

control complier group, which could adversely affect school performance.

To assess school performance, we use administrative test score data of both regular school exams at the end of the term and (for those in grade 8) of the nationally standardized Kenya Certificate of Primary Education (KCPE) exam. We find no impacts on either of these types of test scores.[38] There is also no significant effect on dropout: Column (8) shows the probability that students take the end-of-term exams a year after the intervention (in March 2016),[39] which is not significantly different for those with access to a light.

There are several potential explanations for the lack of impact on test score results. Access to the light and related increase of homework and time spent studying may not have translated into additional learning; the reduced sleep hours may have counteracted the learning effect; the test scores might be a poor measure of underlying student learning; or in the context of prevalent poverty, better lighting and consequently increased study time might not be sufficient to have a real impact on educational achievements, rather a more holistic approach might be necessary to see systemic change regarding educational constraints.

Additional Outcomes

Owning a solar light could have an impact on the guardian's time allocation, shift the activities they used to pursue during the daylight to nighttime, and potentially free up additional time to spend on other productive activities. However, we are not able to find such shifts when analyzing the guardian's time aggregately (see Appendix Table A.3). Guardians that own a working solar light increase the amount of time sleeping by about 18 minutes, but we don't observe any additional shifts across different activities [40].

Another potential impact of owning a solar light is in the guardian's perception of safety in three different aspects: perception of feeling safe inside home, and outside home at night, as well as whether the guardian experienced burn injuries in the 3 months preceding the endline. We can't find a statistically significant impact on either of these 3 outcomes (see Table

[38] Appendix Table A.2 shows results separately by subject

[39] Appendix Table A.9 shows additional measures of exam participation and school attendance. None of them have significant differences between the pooled treatment group, and the control, and there is no consistent direction of the point estimate

[40] In Appendix tables A.4, and A.5, we analyze the guardians' activities by their sub-components. We find a decrease in the amount of time that the guardians spend taking care of their children, sick or elderly, and also attend less to funerals or weddings. However, we found that guardians spend 13 more minutes visiting and/or entertaining friends. Since the information about time use regarding this activity was collected as an aggregated question, we can't distinguish whether the guardians are going out more or inviting more people over to their houses.

A.6). In Appendix Table A.7, we report results for psychological outcomes that are summary indexes, aggregating information across related outcomes (e.g. happiness, satisfaction, optimism, etc.). We found that owning a solar light improves the guardians' perception about their economic situation (Column 5), and increases their level of optimism regarding their future (Column 7). Finally, we also find an impact on the guardians' knowledge regarding solar lamps. Guardians that own a solar light are more likely to know the lamps' charging time, as well as to have more knowledge about solar light brands in the market. However, they are also less likely to know the price of the lamps in the market (see Table A.8).

3.5 Robustness Checks

This section discusses separate treatment effects, controlling for baseline characteristics, excluding gender fixed effects, attrition, accounting for multiple hypothesis testing, and spillover effects.

Separate Treatment Effects

As shown in appendix section D, we reject the null hypothesis of differential impact by type of free light and across treatment arms on most outcomes. Two exceptions are the kerosene light usage and phone charging expenditure: free larger light owners are less likely to use a kerosene light the day before the survey, and reduce their monthly phone charging expenses. Likewise, when comparing across all the treatment arms, we reject the null of same effect in the kerosene light usage the day prior to the survey, and share of homework completed by the students after dark.

Controlling for Baseline Characteristics and excluding Gender Fixed Effects

As an additional robustness check, in Appendix Tables C.5 to C.10, we control for baseline characteristics such as class of the student, connection to the grid, household size, and ownership of a solar lamp. All the results remain robust with the exception of "Number of hours doing homework and personal studies" (see Appendix Table C.10 Column 3). When we add baseline characteristics to the main specification, the point estimate loses statistical significance. Furthermore, in appendix section F, we exclude gender fixed effects. All the results maintain robust to this specification.

Attrition

One potential threat to identification is differential attrition across treatment arms, if students and guardians have different rates of selection into our final sample, our results could be biased. Table C.1 shows whether attrition was differential across treatment groups; guardians that received a higher subsidy voucher and a larger light for free are more likely to participate at endline; students whose guardians redeemed the voucher at the market price are less likely to participate at endline. Table C.2 correlates guardian baseline to endline attrition with observable household characteristics at baseline. The share of female students among attritors is 16.3 percentage points higher than the share of female students among non-attritors. Students with higher test scores are less likely to drop out of the sample. Likewise, guardians who are the student's parents drop out of the sample less often.

We address the differential guardian attrition on the outcomes that are statistically significant using two approaches. First, we use Lee bounds, applying the approach by Lee (2009) to our study involving multiple treatment groups. That is, the share of available observations in each treatment group is equalized to the group with the highest attrition by trimming observations in the top of the distribution (lower bound estimate) and, respectively, in the bottom of the distribution (upper bound estimate). This approach provides upper and lower bounds of the estimates under extreme assumptions about the outcomes of attritors in the respective treatment groups. The lower and upper bounds are reported in Columns (2) and (3) of Table C.3. Both upper and lower bounds remain statistically significant and qualitatively similar to the original estimates shown in Column (1), with the exception of "Eye dryness symptoms for the guardian", whose upper Lee bound of becomes not statistically not significant.

Second, we use inverse probability weighting following Wooldridge (2002) and Wooldridge (2007). This approach recalculates results by reweighting the sample to compensate for the differential attrition between treatment and control groups. The weights are calculated by running a probit regression to predict the probability that based on observable characteristics, a participant is in the non-attritor sample.[41] Thereafter, each individual is weighted with the inverse of this probability. As a result, a larger weight is given to individuals who are less likely to be in the sample, leading participants with characteristics that are underrepresented

[41] In this probit regression, we include the same explanatory variables as in the balance of randomization table (Table 1).

among non-attritors to weigh more. Our main results are very robust to such reweighting and remain statistically significant and qualitatively similar (Column 4) with the exception of the "Number of kerosene lanterns used last month".

Multiple Hypothesis Testing

To further examine the robustness of our results, we adjust for the fact that we test for multiple hypothesis using the false discovery rate adjusted q-values (analogue to the standard p-value). This approach limits the expected proportion of rejections that are false discoveries, that is, type I errors (Benjamini et al., 2006; Anderson, 2008). The false discovery rate adjusted q-values are robust to multiple hypothesis testing (Table C.4, Column 5).

Intention to Treat

The intention to treat (ITT) estimates can be directly derived from the Local Average Treatment Effect (LATE) estimates by dividing the LATE estimates by the share of compliers. In our study, 18.3% of participants are always-takers (i.e. participants in the control group who owned a solar light by the time of the endline survey). In the treatment arms, there are 9.8%, 18.2%, 30.5%, 59.0%, and 59.6% 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 28.1%, 36.4%, 48.8%, 77.3%, 77.8% 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

A potential concern when estimating treatment effects is the presence of spillovers across students and guardians. That is, an intervention may create spillovers when individuals that received the treatment change their behavior and in turn influence the behavior of individuals who didn't receive the treatment with whom they are in social proximity. This poses a challenge because we might underestimate the impacts of the solar light if households which

receive a light through the study share it with households in the control group [42].
There are different mechanisms through which spillovers may influence the treatment effects.

Learning/imitation. The neighbors and/or classmates of the guardians and students that received the solar lights for free or redeemed their voucher, learn from and imitate the treated individuals, and their change in behavior can lead to them purchasing a solar light [43].
Social proximity. This could be the case if they lend the solar lights to other households, if the children bring it to school and share it there, or if members from control group households visit households with a solar light to benefit from their improved lighting.

In addition, children in the control group might benefit from schooling progress of their peers who have access to a solar light.

Based on guardians' responses, only 15 households (1.59%) which received a solar light through the study program indicated that they shared the light with someone else from the same school (i.e. neighbors or friends from the same school, or relatives from the same school). Those who did share it only did so 1.5 times on average during the month prior to the endline survey. It therefore appears unlikely that there are significant spillovers from borrowing or lending the solar light. We also asked children who shared a light with someone else who they shared it with when they used it most recently. While many shared it with other household members, only 11 students (1.2%) shared it with someone outside the household but from the same school. Bringing the light to school was very rare in our context, which differs from Hassan and Lucchino (2016), who hypothesize that the spillover effects they find probably stem from sharing solar lights in schools. As reported by their guardians, only 21 children in our study ever took the light to school. However, survey evidence also suggests that students visit their neighbors' house to benefit from their light source. About 28% of the students in the control group reported going over someone else's house to do homework and personal studies in the week prior to the survey. Among those

[42] To analyze the extent of spillovers in our design, we originally followed the Randomized Saturation (RS) approach proposed by Baird et al. (2014). This approach allows for a valid counterfactual for treated clusters and uses cluster comparisons to identify how spillovers depend on the intensity of the treatment saturation. However, since we reject the null of baseline coefficients jointly equal to zero when examining the baseline balance of our density measure, we decided not to move forward with this analysis.

[43] See sub-section 3.1

students, over 47% mentioned that they did it to have access to a better lighting source. In line with this finding, 28% of the students that were part of the treated households, reported receiving the visit from other children to do personal studies and homework, these children came mostly from the same school as the treated pupil and did it to be assisted by their classmate[44] .

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. On the one hand, they could provide a reliable lighting source to the 759 million without connection to an electric grid. This could be particularly important where grid expansion may not be cost-effective in rural areas in developing countries (Lee et al., 2020). On the other hand, solar lights could contribute to reducing energy expenditures and emissions and improving health outcomes by replacing kerosene-fueled lights. However, existing research suggests that the potential benefits of novel technologies are often overstated (Davis et al., 2014; Fowlie et al., 2018; Allcott and Greenstone, 2012), and that technologies such as cookstoves may remain unused in developing countries in practice depending on factors such as ease of use, maintenance requirements, or suitability to the local context (Hanna et al., 2016; Bensch and Peters, 2015, 2019). We contribute to these questions by providing experimental evidence on the demand for solar lights in developing countries, and the impact of owning a functioning solar light on various outcome dimensions.

We show that demand for solar lights responds strongly to price changes and that reducing transaction and information costs increases demand substantially. Households in our study sample use their solar lights frequently, and usage does not differ systematically across the level of price discounts offered. We find that a working solar light replaces one out of two kerosene lamps in the household on average, contributing to lower kerosene use and reduced emissions. While households spend less on energy if they own a functioning solar light, a

[44] In the context of our randomized field experiment, Donzelli (2018) analyses the adoption and social network effects of portable solar lanterns. The author calculates the neighbours of sampled households within a given spatial radius and analyze the network's role in the adoption decision of solar lanterns. No significant evidence is found for spatial network effects, however, a higher number of study participants with a pupil enrolled in the same school class in an individual's network increases their likelihood of buying the product.

small subsidy may be needed for a solar light investment to pay off from a purely private monetary perspective, given the high interest rates in our study context. Compared to what is typically considered the social cost of carbon (Revesz et al., 2017; Interagency Working Group on Social Cost of Carbon, 2015) and clean energy investments in Europe and the US (Abrell et al., 2017), we find that solar lights appear as a cost-effective intervention with estimated abatement costs per ton of CO_2 at less than USD 10. Concerning individual-level benefits, we find moderately improved health outcomes, particularly for eye health. Our results on students' educational performance are mixed, that is, we find increases in self-reported homework completion and study time but cannot detect a statistically significant effect on test scores.

With regards to the previous literature on solar lights in developing countries, a consensus emerges on the following. Solar lights appear to alleviate eye-related symptoms across studies, but impacts on respiratory health are detected less often (Kudo et al., 2019b; Furukawa, 2017; Grimm et al., 2017; Aevarsdottir et al., 2017). Students who received solar lights self-report having spent more time on homework and more time doing homework after dark. Yet, most studies could not find that this translates into better school performance as measured by test scores (Furukawa, 2014; Kudo et al., 2019a). It is likely that in the context of developing countries and poorer regions this small improvement in study conditions might not be sufficient to attain tangible improvements of educational outcomes. Our study further provides novel contributions such as estimating the impact on emissions and assessing the cost-effectiveness of solar lights.

However, solar lights are not a panacea for energy poverty and climate change. While they provide some improvement over kerosene-fueled lamps, energy access is limited to lighting and, depending on the specific solar kit, mobile phone charging. In turn, solar lights will not suffice as living standards rise; for example, they do not allow households to power appliances like fans or irons. Moreover, cookstoves, not kerosene lamps, are the most important contributor to indoor air pollution, and better cooking solutions must be found to achieve substantial health gains (World Health Organization, 2016). A number of other reasons limit the role of solar lights. While every reduction in warming emissions counts, the contribution of kerosene lamps remains limited. The positive externalities discussed in this paper rely on the fact that solar lights replace kerosene. However, there is evidence that kerosene is increasingly being displaced by battery powered torches, at least in places where it is not subsidized (Bensch et al., 2017). As such, the counterfactual might look different in the future. Finally, maintenance and recycling of old solar lights, especially their batteries, could create new environmental challenges.

Beyond solar lights, future research can test and evaluate other approaches that aim to improve energy access and energy efficiency in developing countries, including the use of renewable energies. This will allow policy makers to compare the cost-effectiveness of different policy options in low-income settings. Studying policy options in developing countries is particularly important given that energy demand and CO_2 emissions are projected to grow most significantly in these countries in the coming years (United Nations, 2020). With regard to solar lighting in particular, future studies can further analyze what drives and constrains different types of consumer demand for such products and whether there are important market failures in contexts that are different from ours. Further, future research could study measures addressing electronic waste in developing countries, which is an important but neglected dimension in the cost-benefit analysis of solar lights. Finally, concerning our findings on indoor air pollution, it would be important to better understand how kerosene use interacts with cooking conditions and what combination of policies are best suited to improving indoor air quality.

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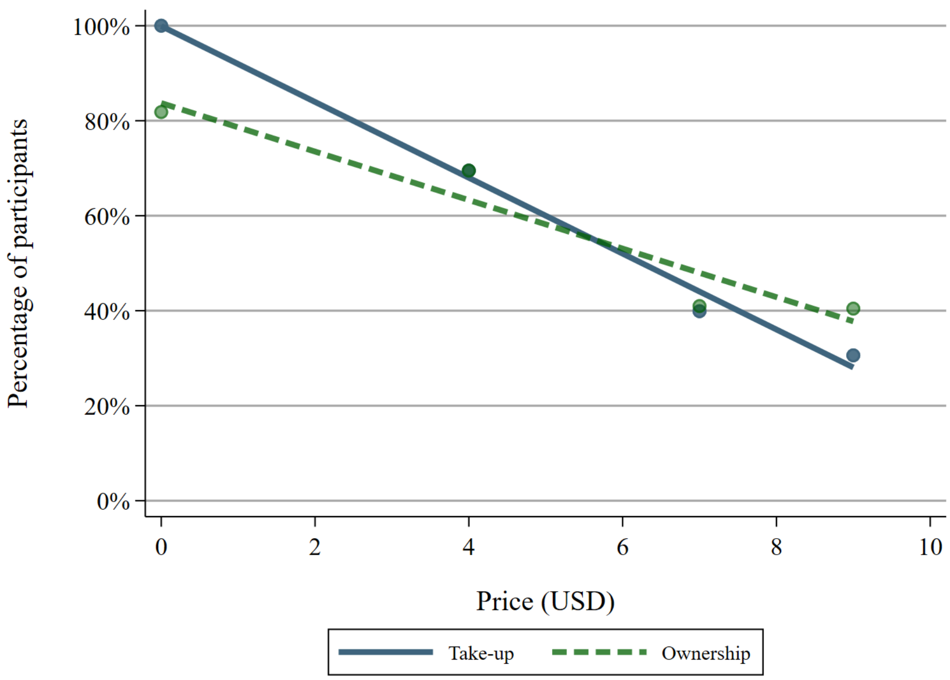
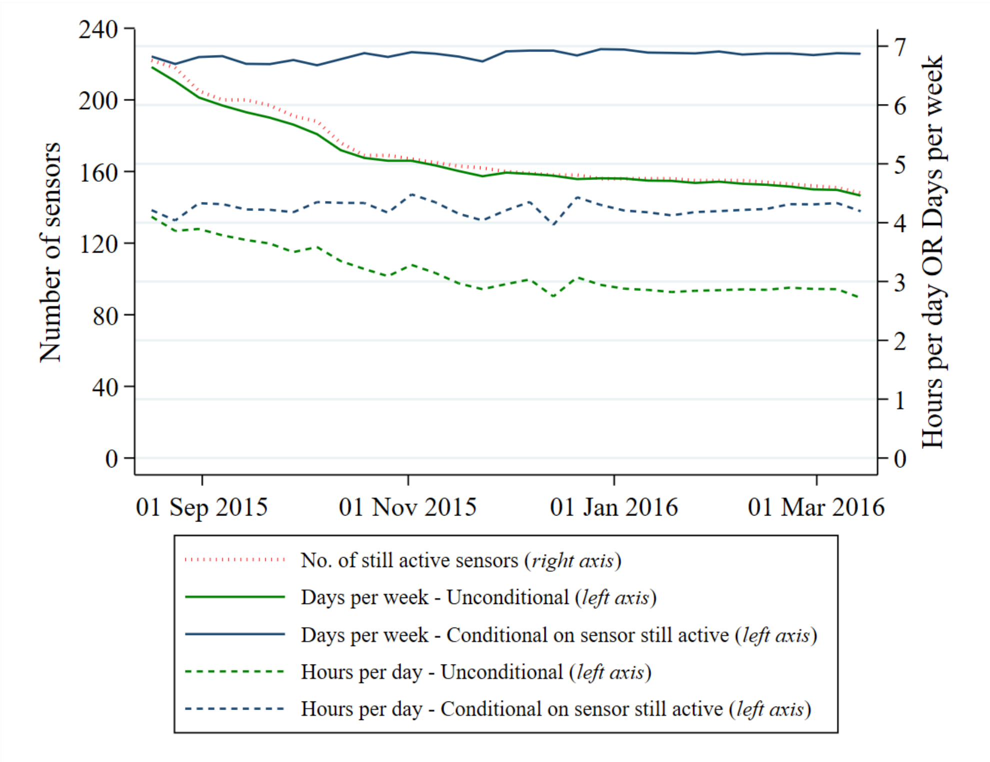
Main Results

Figure 1: Demand for and Ownership of the Basic Solar Light



Notes: This figure plots take-up and ownership of the basic solar light at different prices. Blue points represent the share of individuals who participated in the endline survey and took or bought the light through our intervention at each price (free, and vouchers to purchase a light for USD 4, 7, or 9). Yellow points represent the share of individuals who participated in the endline survey and owned a working solar light at the time of the endline survey. Both curves are fitted based on regressing price on the share of individuals.

Figure 2: Solar Light Usage as Measured by Sensors



Notes: This figure plots solar light usage over time as measured by sensors. On the left vertical axis we have usage in terms of average number of days per week (red lines) or average number of hours per day (blue lines), respectively. For both metrics we provide a conditional on whether the sensor is still active and an unconditional version (i.e. using a constant number of sensors to calculate week-by-week averages). We define sensors as active if they are either turned on in the given week or were turned on at least once before in any prior week and are turned on again in any subsequent week. On the right vertical axis we see the number of unique sensors used for the computation of the conditional averages, while the number of unique sensors used for the unconditional statistics is always 228 (not illustrated). The temporal window depicted here covers the 31-week long period from August 17th 2015 to March 20th 2016, where all weeks are Monday to Sunday.

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)
Average test scores	0.000	0.037	-0.017	-0.039	0.057	0.102	0.028
	[1.000]	(0.063)	(0.068)	(0.060)	(0.085)	(0.080)	(0.051)
Student is in grade 5	0.372	0.022	-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)
Student is female	0.568	-0.087^{*}	-0.011	-0.008	-0.001	-0.088^{*}	-0.040
	[0.496]	(0.043)	(0.035)	(0.045)	(0.036)	(0.042)	(0.029)
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)
Guardian respondent 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 respondent is student's grandparent	0.107	0.017	0.021	-0.009	-0.028	-0.023	-0.004
	[0.310]	(0.021)	(0.028)	(0.026)	(0.017)	(0.023)	(0.015)
Guardian respondent 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)
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)
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 performs agricultural activities	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)
School FE		Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	400	200	209	201	200	200	1,010
F-test for same effect	0.246	0.993	0.627	0.956	0.393	0.253	0.734

Notes: This table presents a balance test of baseline variables across treatment groups. Column (1) shows sample means and standard deviations for the control group. Each row shows estimates from two regressions: Columns (2) to (6) from regressing the baseline variable on dummies for each treatment group; Column (7) on a dummy of all treatment groups pooled. To conduct the F-test, we use stacked regressions with wild bootstrapping procedures. Bootstrapped p-values derived from running 999 iterations. In Column (1), the F-test is for whether all coefficients displayed in Columns (2) to (6) are jointly different from zero; in Columns (2) to (7), for whether coefficients in the respective column are jointly different from zero. Test scores include English, math, science, social studies and Swahili from March 2015. Student from a replacement list indicates whether the student was not in the original list of students and was a replacement student. Standard errors clustered at the household and school level presented in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Usage of Solar Lights

	Number of hours		Days past week	
	Guardians	Students	Guardians	Students
	(1)	(2)	(3)	(4)
Free basic light	3.21***	2.47***	6.61***	6.86***
	(0.17)	(0.22)	(0.24)	(0.29)
High subsidy (USD 4)	3.36***	2.65***	6.73***	6.79***
	(0.22)	(0.21)	(0.11)	(0.30)
Low subsidy (USD 7)	3.53***	2.49***	6.64***	5.79***
	(0.62)	(0.36)	(0.31)	(0.63)
Market price (USD 9)	2.54***	1.74***	6.26***	5.29***
	(0.54)	(0.48)	(0.44)	(0.83)
Free larger light	3.39***	2.32***	6.83***	6.15***
	(0.19)	(0.14)	(0.11)	(0.31)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Number of observations	1,232	904	1,241	905
R-squared	0.63	0.50	0.94	0.62
F-test for same effect	0.595	0.316	0.764	0.178

Notes: Treatment-on-the-treated estimates of having a working solar light on solar light use by the guardian. Each row shows results from a separate TSLS regression following Equations (1) and (2).Column 1 shows the number of hours that the guardian used the solar light the day previous to the endline survey. Column 2 shows the number of hours that the student used the solar light the last time he/she used it. Column 3 shows the number of days that the guardian used the solar light during the past 7 days previous to the endline survey. Column 4 shows the number of days that the student used the solar light during the past week (last Monday to last Sunday previous to the endline survey). The sample of each regression includes households in the control group and the respective treatment group. To conduct the F-test of whether the effect is the same across treatment arms, we use stacked regression. Robust standard errors clustered at the household and school level in parentheses. The number of observations for the students (Columns 2 and 4) is lower because we do not have the response to this question from n=206 students. These missing values occurred because there are cases where the guardian indicated that the household owns a solar light but the the student reported not knowing someone who owns a solar light or not having a relative who owns a solar light and hence the question about the hours of usage was not asked to them. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Impact on Light Use

	(1) Lighting use yesterday guardians (hours)	(2) Lighting use yesterday students (hours)	(3) Lighting interruption last month	(4) Used solar light for homework	(5) Used tin lamp for homework	(6) Used kerosene lantern for homework
Solar light	−0.209	0.396***	−0.388***	1.058***	−0.892***	−0.111***
	(0.143)	(0.115)	(0.047)	(0.057)	(0.053)	(0.033)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	3.136	3.234	0.472	0.000	0.867	0.128
Number of observations	1,313	1,203	1,286	1,051	1,051	1,051
R-squared	-0.02	-0.00	0.16	0.19	0.16	0.01

Notes: Treatment-on-the-treated pooled estimates of having a working solar light on light use following Equations (3) and (4). Columns (1) and (2) show the number of hours during which guardians and students, respectively, used any source of lighting. To measure time use in these variables, the respondents were asked about each time slot of the day. Column (3) shows lighting interruption due to running out of fuel or battery for any of their lighting devices in the past month, reported by the guardian. Columns (4) to (6) show whether the student relied on a solar light, a tin lamp, and a kerosene lantern as a main source of light to do homework, respectively. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Impact on Kerosene Use

	(1) Number of kerosene-fueled lights used last month	(2) Number of tin lamps used last month	(3) Number of kerosene lanterns used last month	(4) Kerosene light used yesterday	(5) Kerosene purchased last month (liters)
Solar light	-0.900^{***}	-0.914^{***}	-0.101^{**}	-0.296^{***}	-1.288^{***}
	(0.155)	(0.095)	(0.042)	(0.034)	(0.224)
School FE	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes
Control complier mean	2.404	2.186	0.268	0.959	2.600
Number of observations	1,313	1,312	1,313	1,307	1,299
R-squared	0.08	0.14	-0.01	0.17	0.04

Notes: Treatment-on-the-treated pooled estimates of having a working solar light on kerosene use following Equations (3) and (4). Column (1) shows the number of kerosene-fueled lights the guardian used in the household in the past month. Columns (2) and (3) show the number of tin lamps and kerosene lanterns that the guardian used in the household in the past month. Column (4) refers to whether any household member used a kerosene-fueled light during the previous evening. Column (5) shows the change in liters of kerosene purchased in the past month at the household level. All variables are from the guardian survey. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Impact on 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	-82.44^{***}	$-2,904^{***}$	$-71,827^{***}$	-85.68^{***}
	(14.41)	(523)	(12,543)	(14.96)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Control complier mean	164.51	5,748	143,276	170.89
Number of observations	1,291	1,291	1,291	1,291
R-squared	0.04	0.04	0.04	0.04

Notes: Treatment-on-the-treated pooled estimates of having a working solar light on household emissions following Equations (3) and (4). The impact on emissions is calculated based on households' kerosene consumption, as reported in Column (5) of Table 4, and the type of kerosene lamp households use, as detailed in Subsection 2.1. As a result, these four columns are linearly dependent among each other. The number of observations differ from those from Column (5) of Table 4 because we don't have information about the type of light used of 8 households. Column (1) shows black carbon, Column (2) CO_2 emissions, Column (3) CO_2-equivalents of the previous two columns combined, and Column (4) particulate matter ($PM_{2.5}$). Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Impact on Energy Expenditures

	(1) Total expenditure	(2) Kerosene	(3) Phone charging	(4) Firewood	(5) Batteries	(6) Charcoal	(7) Electricity bill	(8) Other
Basic light	-1.139^{***}	-0.659^{***}	0.278	-0.383^{**}	0.016	-0.008	-0.278	-0.105
	(0.396)	(0.143)	(0.172)	(0.166)	(0.069)	(0.299)	(0.258)	(0.111)
Larger light	-2.444^{***}	-0.919^{***}	-0.873^{***}	-0.095	0.133	-0.115	-0.432	-0.143
	(0.481)	(0.081)	(0.076)	(0.201)	(0.078)	(0.260)	(0.296)	(0.083)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	4.120	1.685	1.110	0.425	0.276	0.226	0.366	0.034
Number of observations	1,313	1,312	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	-0.01	0.05	-0.01	-0.01	0.00	-0.00	0.00	-0.01
F-test for same effect	0.025	0.114	0.000	0.120	0.238	0.752	0.570	0.602

Notes: Treatment-on-the-treated estimates of having a basic or larger working solar light on households' monthly energy expenditures (in USD) by type of light. Each row results from a separate TSLS regression following Equations (3) and (4). The sample of each regression includes households in the control group and the respective treatment groups. Column (1) shows total energy expenditure, Columns (2) to (8) its components. Column (8) includes expenditures on candles, generator fuel, LPG, sawdust, dung/charcoal mixture, and other types of fuel. To conduct the F-test of whether the effect is the same across types of light, we use stacked regressions with robust standard errors clustered at the household and school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Impact on Health

	Eyes		Respiratory	
	Guardians (1)	Students (2)	Guardians (3)	Students (4)
Solar light	-0.230^{***}	-0.252^{**}	-0.154^{**}	-0.274^{*}
	(0.075)	(0.091)	(0.070)	(0.138)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Number of observations	1,313	1,203	1,313	1,203
R-squared	0.00	-0.00	0.00	-0.01

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

Table 8: Impact on Education

	(1) Homework completion	(2) Share homework after dark	(3) Homework and personal studies (hours)	(4) School (hours)	(5) Sleep (hours)	(6) Average score of 5 subjects	(7) Average score KCPE	(8) Participation in school exams in March 2016
Solar light	0.156***	0.114***	0.318	0.553*	−0.447**	−0.035	−0.075	0.032
	(0.032)	(0.037)	(0.195)	(0.282)	(0.174)	(0.117)	(0.161)	(0.031)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	0.650	0.723	2.435	3.980	8.417	0.039	0.025	0.775
Number of observations	1,051	1,051	1,203	1,203	1,203	1,268	236	1,313
R-squared	-0.01	-0.01	-0.01	0.00	0.00	-0.00	0.00	0.00

Notes: Treatment-on-the-treated pooled estimates of having a working solar light on educational outcomes following Equations (3) and (4). Column (1) shows whether the student was able to complete their homework in the past week. Column (2) shows the share of times the student did homework after dark in the past week. Columns (3) to (5) show results for time use on the day before the endline interview (homework and personal studies, time spent in class, time spent sleeping). Column (6) shows the average final exam scores of the first term in 2016. When the score for a subject is missing, we use the corresponding score from the last term of 2015, when available. The probability of scores missing is balanced across treatment arms (see Appendix Table A.9). Column (7) contains the average score of graduating students who took the national KCPE exam. Column (8) indicates whether the student took at least one of the 5 compulsory exams. Variables in Columns (1) to (5) are from the student survey; variables in Columns (6) to (8) from administrative test score records. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendices

A Additional Outcomes

Table A.1: Impact on Light Use by Lighting Source (hours)

	(1) Total light use	(2) Solar light	(3) Tin lamp	(4) Kerosene lantern	(5) Electricity powered	(6) Battery powered lantern	(7) Cellphone light	(8) Other sources of lighting
Solar light	-0.209	2.12***	-1.83***	-0.271***	-0.099**	-0.055	-0.014	-0.061
	(0.143)	(0.126)	(0.109)	(0.057)	(0.040)	(0.078)	(0.051)	(0.051)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	3.136	0.010	2.495	0.293	0.112	0.080	0.077	0.068
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	-0.02	0.45	0.33	0.01	-0.00	-0.00	-0.00	-0.01

Notes: Treatment-on-the-treated estimates of having a working solar light on the number of hours during which guardians used any source of lighting the day before the endline survey. Each row results from a separate TSLS regression following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Column (1) shows total number of hours using different sources of lighting, Columns (2) to (8) its different sources of lighting. Column (8) includes sources such as firewood, candles, pressurized lantern, and other sources of lighting. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: Impact on Students' Test Scores

	(1) Swahili	(2) Math	(3) English	(4) Science	(5) Social studies	(6) Average score
Panel A: First Term 2016 Exam						
Solar light	-0.046	0.028	-0.045	-0.108	0.012	-0.035
	(0.108)	(0.099)	(0.129)	(0.090)	(0.105)	(0.117)
Number of observations	1,261	1,265	1,260	1,264	1,265	1,268
R-squared	-0.00	0.00	-0.00	-0.01	0.00	-0.00
Panel B: First Term 2016 Exam Without Replacement						
Solar light	-0.105	0.015	-0.090	-0.159	-0.029	-0.121
	(0.116)	(0.110)	(0.124)	(0.100)	(0.124)	(0.124)
Number of observations	1,010	1,004	1,009	1,004	1,004	1,012
R-squared	-0.01	0.00	-0.01	-0.01	-0.00	-0.01
Panel C: KCPE Exam						
Solar light	-0.174	-0.003	0.238	-0.187	-0.252	-0.096
	(0.191)	(0.189)	(0.221)	(0.214)	(0.187)	(0.195)
Number of observations	236	236	236	236	236	236
R-squared	0.00	0.00	-0.00	0.00	0.00	0.00
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Treatment-on-the-treated estimates of having a working solar light on standardized scores of the 5 compulsory subjects following Equations (3) and (4). Panel A shows the students' scores of the first term in 2016. When the score for a subject is missing, we use the corresponding score from the last term of 2015, where available. The probability of scores missing is balanced across treatment arms (see Appendix Table A.9). Panel B shows the students' scores of the first term in 2016 without replacing the missing values. Panel C shows the KCPE score of graduating students who where in grade 7 at baseline who took the national KCPE exam. This variable includes those students who where in grade 7 at baseline and therefore potentially eligible for KCPE. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3: Impact on Time Use of Guardians

	(1) Sleep	(2) Social and recreational activities	(3) Household and care work	(4) Work	(5) Work at night (7pm to 7am)	(6) Travel
Solar light	0.301*	0.401	-0.363*	-0.360	-0.142*	0.126
	(0.154)	(0.401)	(0.207)	(0.444)	(0.071)	(0.137)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	8.593	5.806	4.619	4.245	0.622	0.628
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	-0.02	-0.00	-0.00	-0.00	-0.01	0.00

Notes: Treatment-on-the-treated estimates of having a working solar light on hours of time use by the guardian the day before the endline interview following Equations (3) and (4). Respondents were asked about each time slot of the day. Outcomes in Columns (2) to (6) aggregate different activities. Appendix Tables A.4, and A.5 show the sub-components of these aggregates. Column (5) refers to the work hours (as in Column (4)) done after dark. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Impact on Time Use of Guardians - Household and Care Work, Work and Travel

	(1) Cook prepare food	(2) Clean, dust sweep and other household work	(3) Fetch water and/or firewood	(4) Shop for family	(5) Help homework	(6) Prepare children for school	(7) Care for children sick or elderly	(8) Other household and care work
Solar light	-0.020	-0.017	-0.072	-0.052	0.020	-0.014	-0.176**	-0.030
	(0.139)	(0.129)	(0.082)	(0.082)	(0.044)	(0.037)	(0.067)	(0.054)
Control complier mean	1.841	1.311	0.754	0.305	0.116	0.105	0.091	0.097
R-squared	0.00	-0.00	0.00	-0.00	0.00	-0.00	-0.02	0.00

	(9) Farm work	(10) Non-agricultural work	(11) Herd animals and/or work with livestock	(12) Brew alcohol	(13) Fish or hunt	(14) Travel by foot	(15) Travel by motorized means	(16) Travel by bicycle
Solar light	-0.191	0.009	-0.164	-0.059	0.044	0.045	0.032	0.049
	(0.270)	(0.376)	(0.153)	(0.062)	(0.028)	(0.108)	(0.091)	(0.067)
Control complier mean	2.077	1.218	0.911	0.054	0.000	0.357	0.220	0.051
R-squared	0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Treatment-on-the-treated estimates of having a working solar light on hours of time use by the guardian the day before the endline interview following Equations (3) and (4). To measure time use in this table, the respondents were asked about each time slot of the day. Columns (1) to (8) show the sub-components of Column (3) in Appendix Table A.3, Columns (9) to (13) of Column (4) and Columns (14) to (16) of Column (6). Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5: Impact on Time Use of Guardians - Social and Recreational Activities

	(1) Rest	(2) Socialize with household members	(3) Eat	(4) Participate in community activities	(5) Socialize with non-household members	(6) Funeral and/or wedding activities	(7) Other religious activities	(8) Bathe and/or dress
Solar light	-0.331	-0.010	0.020	0.004	0.075	-0.186**	0.097	0.020
	(0.234)	(0.126)	(0.057)	(0.146)	(0.150)	(0.086)	(0.120)	(0.035)
Control complier mean	2.546	0.715	0.704	0.389	0.351	0.297	0.274	0.211
R-squared	0.01	-0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00
	(9) Pray	(10) Visit and/or entertain friends	(11) Spend time with spouse	(12) Watch TV	(13) Discuss day activities with partner	(14) Listen to radio	(15) Read book	(16) Other
Solar light	0.364*	0.222**	-0.013	0.023	0.008	0.125	0.042	-0.057
	(0.197)	(0.083)	(0.009)	(0.040)	(0.011)	(0.121)	(0.029)	(0.038)
Control complier mean	0.203	0.034	0.013	0.011	0.000	0.000	0.000	0.069
R-squared	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Treatment-on-the-treated estimates of having a working solar light on hours of time use by the guardian the day before the endline interview following Equations (3) and (4). To measure time use in this table, the respondents were asked about each time slot of the day. Columns (1) to (16) show the sub-components of Column (2) in Appendix Table A.3. Robust standard errors clustered at the school level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.6: Impact on Safety

	(1) Feeling safe inside the home at night	(2) Feeling safe outside the home at night	(3) Burn injuries in the past three months
Solar light	-0.040	-0.005	-0.007
	(0.087)	(0.088)	(0.010)
School FE	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes
Control complier mean	3.219	2.986	0.021
Number of observations	1,312	1,250	1,313
R-squared	-0.00	-0.00	0.00

Notes: Treatment-on-the-treated estimates of having a working solar light on perceived safety at night following Equations (3) and (4). The dependent variables in Columns (1) and (2) take the value of 1 if the guardian answered "always" and 0 otherwise (i.e. usually, sometimes, or never). Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: Impact on Psychological Outcomes

	(1) Locus of control	(2) Trust	(3) Happiness	(4) Life satisfaction	(5) Economic situation improved	(6) Future holds good things	(7) Future better than parents	(8) Risk of depression
Solar light	0.034	-0.084	0.103	-0.061	0.287**	-0.026	0.192**	-0.133
	(0.097)	(0.086)	(0.084)	(0.103)	(0.113)	(0.100)	(0.071)	(0.130)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	2.459	0.351	3.789	2.092	1.108	3.839	2.545	1.287
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.00	-0.00	0.00	-0.00	0.01	-0.00	0.01	0.01

Notes: Treatment-on-the-treated estimates of having a working solar light on psychological outcomes expressed in standard deviations following Equations (3) and (4). Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8: Impact on Knowledge About Solar Lights

	(1) Know market price	(2) Know charging time	(3) Know battery run time	(4) Know expected durability	(5) Number of brands known
Solar light	-0.138*	0.261***	-0.031	-0.057	0.456***
	(0.071)	(0.081)	(0.052)	(0.059)	(0.075)
School FE	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes
Control complier mean	0.659	0.428	0.852	0.474	0.461
Number of observations	916	916	916	864	1,313
R-squared	0.01	-0.01	-0.00	0.01	0.09

Notes: Treatment-on-the-treated estimates of having a working solar light on guardians' knowledge about solar lights. Equations (3) and (4). Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: Impact on Sample Screening in Education - Clustered at the School Level

	(1) Probability of taking the KCPE exam	(2) Participation in all 5 exams	(3) Participation in none of the 5 exams	(4) Replaced at least one grade	(5) Number of grades replaced	(6) Attended school last week	(7) Assigned homework last week
Free basic light	−0.025	0.071	−0.097*	−0.090*	−0.429*	−0.012	0.054
	(0.145)	(0.056)	(0.053)	(0.047)	(0.236)	(0.013)	(0.038)
High subsidy (USD 4)	−0.144	−0.032	0.021	−0.035	−0.163	−0.004	0.010
	(0.152)	(0.067)	(0.066)	(0.058)	(0.277)	(0.013)	(0.041)
Low subsidy (USD 7)	−0.709	−0.010	0.014	−0.052	−0.074	−0.014	−0.031
	(0.542)	(0.117)	(0.116)	(0.115)	(0.551)	(0.029)	(0.122)
Market price (USD 9)	−0.248	0.176	−0.196	−0.153	−0.775	0.015	−0.023
	(0.480)	(0.157)	(0.172)	(0.132)	(0.714)	(0.015)	(0.133)
Free larger light	−0.084	−0.006	−0.014	−0.060*	−0.290*	0.004	0.047
	(0.145)	(0.037)	(0.038)	(0.030)	(0.154)	(0.004)	(0.036)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	0.663	0.780	0.225	0.219	1.040	0.998	0.854
Number of observations	370	1,313	1,313	1,313	1,313	1,203	1,198
R-squared	-0.10	-0.01	-0.01	-0.00	-0.01	-0.01	-0.00
F-test for same effect	0.685	0.463	0.454	0.922	0.931	0.373	0.752
F-test of all treatments vs control	0.363	0.711	0.313	0.029	0.033	0.681	0.109

Notes: Treatment-on-the-treated estimates of having a working solar light on variables that are used for sample screening of education outcomes presented in Table 9 and Appendix Table C1. Column (1) shows the probability of attending the KCPE exam and participating in all of the 5 compulsory subjects tested. This variable includes those students who where in grade 7 at baseline and therefore potentially eligible for the KCPE. Column (2) shows the probability that the student took all of the 5 in-class-end-of-term-exams in March 2016. Column (3) shows the probability that the student didn't attend any of the 5 in-class-end-of-term-exams. Column (4) refers to the probability that the student's score is replaced at least once (i.e. that one or more of the 5 subjects that compose the average score are missing). Column (5) refers to the number of subject scores that were replaced for the student. Column (6) shows the probability that the student attended school at least once during the week preceding the endline survey. Column (7) shows the probability that the student was assigned homework at least once in the week before the endline survey. Column (1) is used as a screening question for KCPE average score and KCPE test scores (see Table 8 and Appendix Table A.2), Columns (2) to (5) are screening questions for average test scores and test scores by subject (see Table A.2). Columns (6) and (7) serve as screening questions for outcomes related to homework completion in Table 8, columns (1) and (2). Each row shows results from a separate TSLS regression following Equations (1) and (2). The sample of each regression includes households in the control group and the respective treatment group. F-test at the bottom of the table to assess whether the effect is the same when all the treatments are pooled when compared to the control group. To conduct the F-test of whether the effect is the same across treatment arms, we use stacked regressions with robust standard errors clustered at the household and school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B National Emissions

Table B.1: Cost per Ton of CO_2-eq and Impact on National Emissions

	Free basic light	**High Subsidy (USD 4)**	**Low Subsidy (USD 7)**	**Market Price (USD 9)**	**Free larger light**
Panel A: Our Study					
Reduction in CO_2-eq per household (kg)	6,823.7	4,742.5	2,722.0	2,088.1	6,969.3
Cost per household (USD)	9.00	3.65	0.97	0.17	24.00
Cost per ton of CO_2-eq (USD)	1.32	0.769	0.356	0.082	3.44
Panel B: Projections if Scaled Nationally					
Reduction in CO_2-eq per household (kg)	5,448.3	3,786.6	2,173.4	1,667.2	5,304.3
Cost per household (USD)	9.00	3.65	0.97	0.17	24.00
Cost per ton of CO_2-eq (USD)	1.65	0.963	0.446	0.103	4.52
Panel C: Projections as % of Kenya's Total Emissions in 2019					
Total CO_2-eq reduced in 1 year (Mt)	0.669	0.465	0.267	0.205	0.651
Share of total emissions in 2019 (%)	0.911	0.633	0.363	0.279	0.887
Share of energy emissions in 2019 (%)	2.75	1.91	1.10	0.840	2.67

Notes: Calculations are based on a monthly breakage rate of 0.986%. We assume that failure rates remain the same for an infinite time horizon. All other assumptions are listed in Table G.1. Additional robustness checks for different specifications are shown in Appendix Tables B.2 and B.3. In Appendix G we provide further details about the methodology to estimate the national emissions and CO_2 abatement cost calculations presented in this table.

CO_2 Abatement Cost and CO_2 Reductions at the National Level - Comparison of CO_2-eq Conversion Factors

Different choices in the calculation of a BC CO_2-eq conversion factor have led to a substantial degree of uncertainty in BC estimates. Because of the different channels through which BC affects the climate, as outlined above, these choices primarily hinge on (1) the selection of the time horizon, (2) whether to take as a basis BC's Global Warming Potential (GWP) or Global Temperature Potential (GTP), as well as whether the estimates are defined globally or regionally. We therefore report a range of estimates in Table B.2, taking into account 6 CO_2 equivalence conversion factors. For all factors, we choose a 100-year time horizon, which is more conservative compared to 20-year estimates. We also refer to the more widely used GWP, rather than GTP. Our primary conversion factor stems from the, to date, only regional GWP conversion factor proposed by Bond et al. (2011). Their factor relies on the concept of the specific forcing pulse (SFP) [45]. Taking all potential impacts of BC emissions into account, they estimate that BC generated through fuel-burning activities in Eastern Africa contributes 836 times more to global warming than CO_2 per kg of emissions does during 100 years. We thus multiply the BC emissions by this factor before adding them to the direct CO_2 emissions to get total CO_2-eq emissions. For robustness, we also show results with the SFP factor's upper and lower bound, as well as an alternative factor based on the widely used global GWP for 100 years, and its upper and lower bound. With a factor of 900 for GWP 100-years, our primary and alternative factors are similar, and we use the more conservative of the two. With the upper and lower bounds, the 6 illustrated conversion factors range from 120 to 1800.

[45] Bond et al. (2011) define the SFP for energy added within a region, as the energy added to a region by one gram of a species (in this case BC) emitted in a given region.

Table B.2: Impact on National Emissions with Different CO_2-eq Conversion Factors

Infinite lamp life span Factor	(1) CO_2 only, no BC	(2) CO_2-eq SFP East Africa (E.A.)	(3) CO_2-eq SFP E.A. lower bound	(4) CO_2-eq SFP E.A. upper bound	(5) CO_2-eq GWP 100	(6) CO_2-eq GWP 100 lower bound	(7) CO_2-eq GWP 100 upper bound
Factor value	0	836	371	1300	900	120	1800
Panel A: Our Study							
Reduction in CO_2-eq per household (kg)	236.7	6,823.7	3,159.9	10,479.7	7,328.0	1,182.2	14,419.2
Cost per household (USD)	9.00	9.00	9.00	9.00	9.00	9.00	9.00
Cost per ton of CO_2-eq (USD)	38.0	1.32	2.85	0.859	1.23	7.61	0.624
Panel B: Projections if Scaled Nationally							
Reduction in CO_2-eq per household (kg)	245.7	5,448.3	2,554.5	8,335.9	5,846.6	992.4	11,447.5
Cost per household (USD)	9.00	9.00	9.00	9.00	9.00	9.00	9.00
Cost per ton of CO_2-eq (USD)	36.6	1.65	3.52	1.08	1.54	9.07	0.786
Panel C: Projections as % of Kenya's Total Emissions in 2019							
Total CO_2-eq reduced in 1 year (Mt)	0.036	0.669	0.317	1.02	0.717	0.127	1.40
Share of total emissions in 2019 (%)	0.049	0.911	0.431	1.39	0.977	0.172	1.91
Share of energy emissions in 2019 (%)	0.146	2.75	1.30	4.19	2.94	0.519	5.74

Notes: This table shows the calculations of CO_2 abatement costs under the free distribution of a basic solar light, using different CO_2-eq conversion factors. Calculations are based on a monthly breakage rate of 0.986%. We assume that failure rates remain the same for an infinite time horizon. All other assumptions are listed in Table G.1. In Appendix G we provide further details about the methodology to estimate the national emissions and cost abatement calculations presented in this table.

Table B.3: Cost per Ton of CO_2-eq and Impact on National Emissions - Comparison of different life spans

	2 years	**5 years**	**7 years**	**10 years**	**∞ years**
Panel A: Our Study					
Reduction in CO_2-eq per household (kg)	1,392.47	3,001.46	3,795.99	4,683.95	6,823.73
Cost per ton of CO_2-eq (USD)	6.46	3.00	2.37	1.92	1.32
Panel B: Projections if Scaled Nationally					
Reduction in CO_2-eq per household (kg)	1,104.28	1,910.33	3,351.85	5,503.58	5,448.30
Cost per ton of CO_2-eq (USD)	8.15	4.71	2.69	1.64	1.65

Notes: This table shows the calculations of CO_2 abatement costs under the free distribution of a basic solar light, assuming different life spans for the solar light.Calculations are based on a monthly breakage rate of 0.986%. All other assumptions are listed in Table G.1. In Appendix G we provide further details about the methodology to estimate the national emissions and CO_2 abatement cost calculations presented in this table.

C Robustness Checks

Attrition

Table C.1: Attrition - Regression on Treatment Group Dummies

	(1) Endline attrition students	(2) Endline attrition guardians
Free basic light	−0.010	−0.018
	(0.024)	(0.021)
High subsidy (USD 4)	0.014	−0.033
	(0.027)	(0.020)
Low subsidy (USD 7)	0.033	−0.014
	(0.029)	(0.016)
Market price (USD 9)	0.047**	−0.010
	(0.022)	(0.017)
Free larger light	−0.005	−0.039**
	(0.028)	(0.018)
School FE	Yes	Yes
Respondent gender	Yes	Yes
Control mean	0.088	0.083
Number of observations	1,332	1,410
F-test of all treatments vs control	0.407	0.098

Notes: Column (1) shows endline attrition for students, that is, students that didn't participate at the endline survey but whose guardians participated at their respective endline survey. Column (2) shows endline attrition for guardians, that is, guardians that didn't participate at the endline survey. Coefficients in Columns (1) and (2) are estimated using stacked regressions and are equivalent to running each column as a separate regression. The raw shares of endline attrition for the full sample (without school fixed effects) are 9.7% for students and 7% for guardians. The F-test at the bottom of the table tests whether the coefficient of all treatment dummies against the control group is different from zero. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.2: Attrition - Baseline Characteristics of Non-Attritors versus Attritors

	Guardian attrition		**Student attrition**	
	(1)	(2)	(3)	(4)
	Non - attritors	Difference attritors	Non - attritors	Difference attritors
Connection to the grid	0.014	-0.003	0.015	-0.009
	[0.119]	(0.010)	[0.121]	(0.009)
Household owns a solar light	0.058	0.027	0.060	-0.018
	[0.234]	(0.023)	[0.237]	(0.019)
Average test scores (baseline)	0.028	-0.025	0.054	-0.322***
	[0.986]	(0.082)	[0.988]	(0.075)
Student is in grade 5	0.343	0.032	0.344	-0.020
	[0.475]	(0.053)	[0.475]	(0.033)
Student is in grade 6	0.374	-0.036	0.377	-0.040
	[0.484]	(0.053)	[0.485]	(0.038)
Student is in grade 7	0.283	0.004	0.279	0.060
	[0.451]	(0.035)	[0.449]	(0.041)
Student is female	0.542	-0.034	0.530	0.163***
	[0.498]	(0.040)	[0.499]	(0.047)
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	-0.186***
	[0.406]	(0.039)	[0.395]	(0.035)
Guardian respondent is student's grandparent	0.104	-0.019	0.098	0.052*
	[0.306]	(0.028)	[0.298]	(0.026)
Guardian respondent is female	0.672	0.009	0.673	-0.019
	[0.470]	(0.059)	[0.469]	(0.037)
Student from replacement list	0.132	0.043	0.133	0.010
	[0.338]	(0.034)	[0.340]	(0.028)
Baseline guardian survey at school	0.947	-0.052	0.949	-0.033
	[0.225]	(0.041)	[0.219]	(0.023)
Household size	6.82	-0.042	6.83	-0.086
	[2.15]	(0.250)	[2.14]	(0.211)
Household performs agricultural activities	0.988	0.003	0.989	-0.022
	[0.110]	(0.013)	[0.103]	(0.013)
School FE		Yes		Yes

Notes: Columns (1) and (3) show the means of baseline characteristics for non-attritors with the standard deviation in square brackets. Columns (2) and (4) show the difference in these characteristics between non-attritors and attritors for guardians' attrition and students' attrition, respectively. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.3: Attrition - Lee Bounds and IPW

	(1)	(2)	(3)	(4)
		Lee Bounds		**Inverse**
	Non-adjusted estimates	Lower bound	Upper bound	**Probability Weighted**
Lighting use (hours) - student	0.396***	0.388***	0.386***	0.343***
	(0.115)	(0.115)	(0.102)	(0.111)
Student relies on solar light to do homework	1.058***	1.070***	1.070***	1.068***
	(0.057)	(0.058)	(0.059)	(0.064)
Student relies on tin lamp to do homework	−0.892***	−0.903***	−0.925***	−0.904***
	(0.053)	(0.058)	(0.055)	(0.052)
Student relies on kerosene lantern to do homework	−0.111***	−0.068***	−0.111***	−0.115***
	(0.033)	(0.022)	(0.033)	(0.037)
Eye dryness - student	−0.252**	−0.268**	−0.253**	−0.312***
	(0.091)	(0.104)	(0.092)	(0.087)
Respiratory symptoms - student	−0.274*	−0.308**	−0.278*	−0.284*
	(0.138)	(0.126)	(0.138)	(0.142)
Homework completion	0.156***	0.156***	0.157***	0.182***
	(0.032)	(0.033)	(0.034)	(0.035)
Share homework completed after dark	0.114***	0.116***	0.118***	0.105**
	(0.037)	(0.038)	(0.037)	(0.040)
Hours in school	0.553*	0.557**	0.564*	0.466
	(0.282)	(0.255)	(0.289)	(0.289)
Hours of sleep - student	−0.447**	−0.448**	−0.348**	−0.367**
	(0.174)	(0.158)	(0.124)	(0.158)
Probability of light interruption	−0.388***	−0.437***	−0.379***	−0.391***
	(0.047)	(0.046)	(0.051)	(0.053)
Number of kerosene-fueled lights used last month - guardian	−0.900***	−1.117***	−0.801***	−1.095***
	(0.155)	(0.096)	(0.172)	(0.106)
Number of tin lamps used last month - guardian	−0.914***	−1.028***	−0.833***	−1.019***
	(0.095)	(0.083)	(0.109)	(0.095)
Number of kerosene lanterns used last month - guardian	−0.101**	−0.168***	−0.072*	−0.075
	(0.042)	(0.046)	(0.040)	(0.049)
Kerosene light used yesterday - guardian	−0.296***	−0.323***	−0.251***	−0.304***
	(0.034)	(0.041)	(0.046)	(0.033)
Kerosene purchased (l/month)	−1.288***	−1.468***	−1.186***	−1.440***
	(0.224)	(0.225)	(0.235)	(0.255)
CO_2-eq emissions (kg/month)	−71,826.97***	−82,036.85***	−66,667.59***	−81,788.1***
	(12,543)	(12,904.43)	(13,370.64)	(14,066.2)
$PM_{2.5}$ emissions	−85.676***	−97.844***	−79.520***	−97.549***
	(14.961)	(15.388)	(15.947)	(16.779)
Eye dryness - guardian	−0.230***	−0.338***	−0.159*	−0.256***
	(0.075)	(0.070)	(0.086)	(0.078)
Respiratory symptoms - guardian	−0.154**	−0.290***	−0.094	−0.123*
	(0.070)	(0.075)	(0.089)	(0.070)

Notes: Column (1) to (4) show coefficients and standard errors from a two-stage least square regression of the respective outcome variable of the students and guardians on the *solar_works* indicator using treatment assignments as an instrument. Specification includes school fixed effects and respondent gender. Column (1) shows results restricting the sample to individuals in households that participated at endline (Lee bounds) or reweight (IPW) observations as is done in Column (2) to (4). Column (2) and (3) apply the idea of Lee bounds to multiple treatment groups. That is, the share of available observations in each treatment group is equalized to the group with the highest attrition by trimming observations in the top of the distribution (lower bound estimate) and, respectively, in the bottom of the distribution (upper bound estimate). Column (4) shows estimates calculated with Inverse Probability Weights (IPWs). The weights are calculated from the variables used in the balance table via a probit regression. We don't include the student's age because we don't have that information for the student attritors. Robust standard errors clustered at the school level in parentheses.

ITT & False Discovery Rates

Table C.4: Intention to Treat and Adjustments for Multiple Hypothesis Testing

	(1) Control [S.D.]	(2) ITT (S.E.)	(3) LATE (S.E.)	(4) P-value LATE	(5) Q-value LATE
(1) Lighting use students (hours)	3.33	0.182**	0.396***	0.0006	0.0010
	[1.35]	(0.086)	(0.115)		
(2) Student relies on solar light to do homework	0.084	0.498***	1.06***	0.0000	0.0010
	[0.279]	(0.029)	(0.057)		
(3) Student relies on tin lamp to do homework	0.749	-0.406***	-0.892***	0.0000	0.0010
	[0.434]	(0.038)	(0.053)		
(4) Student relies on kerosene lantern to do homework	0.104	-0.054**	-0.111***	0.0008	0.0010
	[0.305]	(0.024)	(0.033)		
(5) Eye dryness - student	-0.000	-0.149*	-0.252**	0.0054	0.0030
	[1.00]	(0.072)	(0.091)		
(6) Respiratory symptoms - student	0.000	-0.093	-0.274*	0.0474	0.0130
	[1.000]	(0.085)	(0.138)		
(7) Homework completion	0.693	0.068**	0.156***	0.0000	0.0010
	[0.462]	(0.024)	(0.032)		
(8) Share homework completed after dark	0.770	0.044*	0.114***	0.0021	0.0020
	[0.339]	(0.022)	(0.037)		
(9) Hours in school	4.50	0.228	0.553*	0.0499	0.0130
	[2.97]	(0.147)	(0.282)		
(10) Hours of sleep - student	8.36	-0.214**	-0.447**	0.0103	0.0040
	[1.61]	(0.099)	(0.174)		
(11) Probability of light interruption	0.445	-0.209***	-0.388***	0.0000	0.0010
	[0.498]	(0.033)	(0.047)		
(12) Number of kerosene-fueled lights used last month - guardian	2.24	-0.445***	-0.900***	0.0000	0.0010
	[1.14]	(0.073)	(0.155)		
(13) Number of tin lamps used last month - guardian	2.00	-0.414***	-0.914***	0.0000	0.0010
	[0.974]	(0.067)	(0.095)		
(14) Number of kerosene lanterns used last month - guardian	0.240	-0.061*	-0.101**	0.0165	0.0060
	[0.525]	(0.033)	(0.042)		
(15) Kerosene light used yesterday - guardian	0.912	-0.157***	-0.296***	0.0000	0.0010
	[0.283]	(0.019)	(0.034)		
(16) Kerosene purchased (l/month)	2.08	-0.520***	-1.29***	0.0000	0.0010
	[2.49]	(0.143)	(0.224)		
(17) CO_2-eq emissions (kg/month)	115,581	-28,108***	-71,827***	0.0000	0.0010
	[145,456]	(8,128)	(12,543)		
(18) $PM_{2.5}$ emissions	138	-33.54***	-85.68***	0.0000	0.0010
	[173]	(9.69)	(14.96)		
(19) Eye dryness - guardian	-0.000	-0.144***	-0.230***	0.0023	0.0020
	[1.000]	(0.048)	(0.075)		
(20) Respiratory symptoms - guardian	0.000	-0.059	-0.154**	0.0288	0.0090
	[1.000]	(0.051)	(0.070)		

Notes: Table includes main outcomes from the study. We control for school fixed effects and respondent gender. All the standard errors are clustered at the school level. No other control variables are used. Column (1) reports the mean from the control group with SD in squared brackets. Column (2) reports intention to treat (ITT) regression estimates with robust standard errors clustered at the school level. Column (3) reports Local Average Treatment Effect (LATE) estimates with robust standard errors in parentheses. These are the point estimates reported in the main specification. Column (4) shows standard p-values for LATE estimates. Column (5) reports the false discovery rate (FDR)-adjusted Q-values following Anderson (2008) associated with the p-values in Column (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Impacts with Controls

Table C.5: Impact on Light Use with Controls

	(1) Lighting use yesterday guardians (hours)	(2) Lighting use yesterday students (hours)	(3) Lighting interruption last month	(4) Used solar light for homework	(5) Used tin lamp for homework	(6) Used kerosene lantern for homework
Solar light	−0.211	0.386***	−0.387***	1.065***	−0.900***	−0.112***
	(0.136)	(0.120)	(0.047)	(0.060)	(0.057)	(0.033)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	3.137	3.244	0.472	0.000	0.874	0.129
Number of observations	1,313	1,203	1,286	1,051	1,051	1,051
R-squared	0.00	0.04	0.16	0.21	0.17	0.01

Notes: Treatment-on-the-treated estimates of having a working solar light on light use following Equations (3) and (4). Columns (1) and (2) show the number of hours during which guardians and students, respectively, used any source of lighting. To measure time use in these variables, the respondents were asked about each time slot of the day. Column (3) shows lighting interruption due to running out of fuel or battery for any of their lighting devices in the past month, reported by the guardian. Columns (4) to (6) show whether the student relied on a solar light, a tin lamp, or a kerosene lantern as a main source of light for doing their homework, respectively. In all the specifications we control for baseline characteristics such as class of the student, connection to the grid, household size and ownership of a solar light. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.6: Impact on Kerosene Use with Controls

	(1) Number of kerosene-fueled lights used last month	(2) Number of tin lamps used last month	(3) Number of kerosene lanterns used last month	(4) Kerosene light used yesterday	(5) Kerosene purchased last month (liters)
Solar light	-0.886^{***}	-0.901^{***}	-0.103^{**}	-0.292^{***}	-1.272^{***}
	(0.161)	(0.090)	(0.041)	(0.033)	(0.221)
School FE	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Control complier mean	2.390	2.172	0.270	0.955	2.584
Number of observations	1,313	1,312	1,313	1,307	1,299
R-squared	0.10	0.18	-0.00	0.20	0.05

Notes: Treatment-on-the-treated estimates of having a working solar light on kerosene use and energy expenditure with controls following Equations (3) and (4). Column (1) shows the number of kerosene-fueled lights the guardian used in the household in the past month. Columns (2) and (3) show the number of tin lamps and kerosene lanterns that the guardian used in the household in the past month. Column (1) is the sum of tin lamps, kerosene lanterns, and pressurized lamps. Column (4) refers to whether any household member used a kerosene-fueled light in the previous evening. Column (5) shows the change in liters of kerosene purchased in the past month at the household level. In all the specifications we control for baseline characteristics such as class of the student, connection to the grid, household size and ownership of a solar lamp. All variables are from the guardian survey. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.7: Impact on Emissions with Controls

	(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	-81.38^{***}	$-2,868^{***}$	$-70,897^{***}$	-84.57^{***}
	(14.02)	(516)	(12,211)	(14.56)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Control complier mean	163.44	5,711	142,346	169.79
Number of observations	1,291	1,291	1,291	1,291
R-squared	0.05	0.05	0.05	0.05

Notes: Treatment-on-the-treated estimates of having a working solar light on household emissions with controls following Equations (3) and (4). The impact on emissions is calculated based on households' kerosene consumption, as reported in Column (3) of Table 4, and the type of kerosene lamp households use, as detailed in Subsection 2.1. As a result, these four columns are linearly dependent among each other. Column (1) shows black carbon, Column (2) CO_2 emissions, Column (3) CO_2-equivalents of the previous two columns combined, and Column (4) particulate matter ($PM_{2.5}$). In all the specifications we control for baseline characteristics such as class of the student, connection to the grid, household size and ownership of a solar light. All variables are from the guardian survey. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.8: Impact on Expenditures with Controls

	(1) Total expenditure	(2) Kerosene	(3) Phone charging	(4) Firewood	(5) Batteries	(6) Charcoal	(7) Electricity bill	(8) Other
Basic light	-1.210^{***}	-0.654^{***}	0.301	-0.394^{**}	0.013	-0.005	-0.354	-0.118
	(0.383)	(0.148)	(0.176)	(0.168)	(0.069)	(0.298)	(0.268)	(0.108)
Larger light	-2.253^{***}	-0.931^{***}	-0.894^{***}	-0.079	0.135^{*}	-0.093	-0.256	-0.133
	(0.384)	(0.080)	(0.080)	(0.193)	(0.077)	(0.255)	(0.190)	(0.081)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	4.114	1.683	1.102	0.427	0.278	0.225	0.366	0.036
Number of observations	1,313	1,312	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.07	0.06	0.02	-0.00	0.01	0.00	0.20	0.01
F-test for same effect	0.028	0.090	0.000	0.090	0.218	0.793	0.482	0.820

Notes: Treatment-on-the-treated estimates of having a working solar light on households' monthly energy expenditures (in USD) by type of light. Each row results from a separate TSLS regression following Equations (3) and (4). The sample of each regression includes households in the control group and the respective treatment groups. Column (1) shows total energy expenditure, Columns (2) to (8) its components. Column (8) includes expenditures on candles, generator fuel, LPG, sawdust, dung/charcoal mixture, and other types of fuel. In all the specifications we control for baseline characteristics such as class of the student, connection to the grid, household size and ownership of a solar light. All variables are from the guardian survey. To conduct the F-test of whether the effect is the same across types of light, we use stacked regressions with robust standard errors clustered at the household and school level (reported in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.9: Impact on Health with Controls

	Eyes		Respiratory	
	Guardians (1)	Students (2)	Guardians (3)	Students (4)
Solar light	-0.229^{***}	-0.249^{**}	-0.156^{**}	-0.278^{*}
	(0.076)	(0.088)	(0.070)	(0.140)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of observations	1,313	1,203	1,313	1,203
R-squared	0.01	0.00	0.01	-0.00

Notes: Treatment-on-the-treated estimates of having a working solar light on health with controls following Equations (3) and (4). Columns (1) and (2) show an index of eye-related symptoms such as dryness, grittiness, redness, etc. based on Lee et al. (2002). Columns (3) and (4) show an index of respiratory symptoms such as shortness of breath, asthma, cough, etc. based on Bates et al. (2013) and The European Community Respiratory Health Survey II Steering Committee (2002). Effects are expressed in standard deviations. Higher values indicate more symptoms. In all the specifications we control for baseline characteristics such as class of the student, connection to the grid, household size and ownership of a solar lamp. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.10: Impact on Education with Controls

	(1) Homework completion	(2) Share homework after dark	(3) Homework and personal studies (hours)	(4) School (hours)	(5) Sleep (hours)	(6) Average score of 5 subjects	(7) Average score KCPE	(8) Participation in school exams in March 2016
Solar light	0.154***	0.112***	0.312	0.534*	−0.438**	−0.047	−0.061	0.032
	(0.034)	(0.036)	(0.183)	(0.281)	(0.178)	(0.112)	(0.144)	(0.031)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	0.652	0.724	2.441	3.998	8.408	0.050	0.011	0.775
Number of observations	1,051	1,051	1,203	1,203	1,203	1,268	236	1,313
R-squared	0.00	-0.00	0.04	0.03	0.05	0.07	0.01	0.00

Notes: Treatment-on-the-treated estimates of having a working solar light on educational outcomes with controls following Equations (3) and (4). Column (1) shows whether the student was able to complete the homework in the past week. Column (2) shows the share of times the student did homework after dark in the past week. Columns (3) to (5) show results for time use on the day before the endline interview (homework and personal studies, time spent in class, time spent sleeping). Column (6) shows the average final exam scores of the first term in 2016. When the score for a subject is missing, we use the corresponding score from the last term of 2015, when available. The probability of scores missing is balanced across treatment arms (see Appendix Table A.9). Column (7) contains the average score of graduating students who took the national KCPE exam. Column (8) indicates whether the student took at least one of the 5 compulsory exams. Variables in Columns (1) to (5) are from the student survey; variables in Columns (6) to (8) from administrative test score records. In all the specifications we control for baseline characteristics such as class of the student, connection to the grid, household size and ownership of a solar lamp. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Separate Treatment Effect Estimates

Impacts with pooled basic lights vs. larger light

Table D.1: Impact on Light Use - Basic vs. Larger Light

	(1) Lighting use yesterday guardians (hours)	(2) Lighting use yesterday students (hours)	(3) Lighting interruption last month	(4) Used solar light for homework	(5) Used tin lamp for homework	(6) Used kerosene lantern for homework
Basic light	-0.221^{*}	0.391^{***}	-0.379^{***}	1.095^{***}	-0.916^{***}	-0.098^{**}
	(0.125)	(0.126)	(0.060)	(0.059)	(0.059)	(0.036)
Larger light	-0.288	0.413^{***}	-0.413^{***}	1.004^{***}	-0.854^{***}	-0.115^{***}
	(0.199)	(0.144)	(0.050)	(0.067)	(0.063)	(0.035)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	3.136	3.234	0.472	0.000	0.867	0.128
Number of observations	1,313	1,203	1,286	1,051	1,051	1,051
R-squared	-0.02	-0.00	0.15	0.15	0.11	0.01
F-test for same effect	0.734	0.856	0.491	0.176	0.227	0.401

Notes: Treatment-on-the-treated estimates of having a working solar light on light use following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Columns (1) and (2) show the number of hours during which guardians and students, respectively, used any source of lighting. To measure time use in these variables, the respondents were asked about each time slot of the day. Column (3) shows lighting interruption due to running out of fuel or battery for any of their lighting devices in the past month, reported by the guardian. Columns (4) to (6) show whether the student relied on a solar light, a tin lamp, or a kerosene lantern as a main source of light for doing their homework, respectively. For outcomes in which the guardian and the student report usage and time use about the day before the survey, we control for day of the week fixed effects. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.2: Impact on Kerosene Use - Basic vs. Larger Light

	(1) Number of kerosene-fueled lights used last month	(2) Number of tin lamps used last month	(3) Number of kerosene lanterns used last month	(4) Kerosene light used yesterday	(5) Kerosene purchased last month (liters)
Basic light	-1.036^{***}	-0.932^{***}	-0.111^{**}	-0.250^{***}	-1.253^{***}
	(0.125)	(0.132)	(0.052)	(0.035)	(0.288)
Larger light	-0.782^{***}	-0.879^{***}	-0.106	-0.358^{***}	-1.220^{***}
	(0.252)	(0.123)	(0.066)	(0.048)	(0.218)
School FE	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes
Control complier mean	2.404	2.186	0.268	0.959	2.600
Number of observations	1,313	1,312	1,313	1,307	1,299
R-squared	0.08	0.14	-0.01	0.19	0.04
F-test for same effect	0.364	0.740	0.949	0.064	0.896

Notes: Treatment-on-the-treated estimates of having a working solar light on kerosene use following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Column (1) shows the number of kerosene-fueled lights the guardian used in the household in the past month. Columns (2) and (3) show the number of tin lamps and kerosene lanterns that the guardian used in the household in the past month. Column (1) is the sum of tin lamps, kerosene lanterns, and pressurized lamps. Column (4) refers to whether any household member used a kerosene-fueled light in the previous evening. Column (5) shows the change in liters of kerosene purchased in the past month at the household level. All variables are from the guardian survey. For outcomes in which the guardian reports usage and time use about the day before the survey, we control for day of the week fixed effects. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.3: Impact on Emissions - Basic vs. Larger Light

	(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)
Basic light	-77.67^{***}	$-2,799^{***}$	$-67,735^{***}$	-80.80^{***}
	(18.75)	(647)	(16,301)	(19.44)
Larger light	-79.38^{***}	$-2,811^{***}$	$-69,170^{***}$	-82.51^{***}
	(13.51)	(512)	(11,770)	(14.04)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Control complier mean	164.51	5,748	143,276	170.89
Number of observations	1,291	1,291	1,291	1,291
R-squared	0.04	0.04	0.04	0.04
F-test for same effect	0.916	0.983	0.918	0.919

Notes: Treatment-on-the-treated estimates of having a working solar light on household emissions following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. The impact on emissions is calculated based on households' kerosene consumption, as reported in Column (3) of Table 4, and the type of kerosene lamp households use, as detailed in Subsection 2.1. As a result, these four columns are linearly dependent among each other. Column (1) shows black carbon, Column (2) CO_2 emissions, Column (3) CO_2-equivalents of the previous two columns combined, and Column (4) particulate matter ($PM_{2.5}$). For outcomes in which the guardian reports usage and time use about the day before the survey, we control for day of the week fixed effects. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.4: Impact on Energy Expenditures - Pooled

	(1) Total expenditure	(2) Kerosene	(3) Phone charging	(4) Firewood	(5) Batteries	(6) Charcoal	(7) Electricity bill	(8) Other
Solar light	-1.759^{***}	-0.829^{***}	-0.328^{***}	-0.259	0.064	-0.016	-0.276	-0.117
	(0.344)	(0.081)	(0.108)	(0.159)	(0.056)	(0.237)	(0.214)	(0.080)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	4.120	1.685	1.110	0.425	0.276	0.226	0.366	0.034
Number of observations	1,313	1,312	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	-0.01	0.06	-0.01	-0.01	0.00	-0.00	0.00	-0.01

Notes: Treatment-on-the-treated estimates of having a working solar light on households' monthly energy expenditures (in USD) following Equations (3) and (4). Column (1) shows total energy expenditure, Columns (2) to (8) its components. Column (8) includes expenditures on candles, generator fuel, LPG, sawdust, dung/charcoal mixture, and other types of fuel. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.5: Impact on Health - Basic vs. Larger Light

	Eyes		Respiratory	
	Guardians (1)	Students (2)	Guardians (3)	Students (4)
Basic light	-0.260^{**}	-0.243^{**}	-0.163^{*}	-0.259
	(0.107)	(0.095)	(0.093)	(0.152)
Larger light	-0.225^{**}	-0.289^{**}	-0.126	-0.245
	(0.103)	(0.137)	(0.092)	(0.171)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Number of observations	1,313	1,203	1,313	1,203
R-squared	0.00	0.00	0.00	-0.00
F-test for same effect	0.810	0.728	0.765	0.930

Notes: Treatment-on-the-treated estimates of having a working solar light on health following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Columns (1) and (2) show an index of eye-related symptoms such as dryness, grittiness, redness, etc. based on Lee et al. (2002). Columns (3) and (4) show an index of respiratory symptoms such as shortness of breath, asthma, cough, etc. based on Bates et al. (2013) and The European Community Respiratory Health Survey II Steering Committee (2002). Effects are expressed in standard deviations. Higher values indicate more symptoms. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.6: Impact on Education - Basic vs. Larger Light

	(1) Homework completion	(2) Share homework after dark	(3) Homework and personal studies (hours)	(4) School (hours)	(5) Sleep (hours)	(6) Average score of 5 subjects	(7) Average score KCPE	(8) Participation in school exams in March 2016
Basic light	0.170***	0.132***	0.315	0.788**	−0.514**	−0.038	−0.066	0.052
	(0.044)	(0.043)	(0.195)	(0.358)	(0.210)	(0.149)	(0.203)	(0.038)
Larger light	0.139***	0.096**	0.311	0.334	−0.416*	−0.031	0.007	0.014
	(0.046)	(0.037)	(0.225)	(0.288)	(0.203)	(0.101)	(0.250)	(0.038)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	0.650	0.723	2.435	3.980	8.417	0.039	0.025	0.775
Number of observations	1,051	1,051	1,203	1,203	1,203	1,268	236	1,313
R-squared	-0.01	-0.01	-0.01	0.00	0.00	-0.00	-0.00	0.00
F-test for same effect	0.607	0.386	0.977	0.123	0.645	0.951	0.821	0.414

Notes: Treatment-on-the-treated estimates of having a working solar light on educational outcomes following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Column (1) shows whether the student was able to complete the homework in the past week. Column (2) shows the share of times the student did homework after dark in the past week. Columns (3) to (5) show results for time use on the day before the endline interview (homework and personal studies, time spent in class, time spent sleeping). Column (6) shows the average final exam scores of the first term in 2016. When the score for a subject is missing, we use the corresponding score from the last term of 2015, when available. The probability of scores missing is balanced across treatment arms (see Appendix Table A.9). Column (7) contains the average score of graduating students who took the national KCPE exam. Column (8) indicates whether the student took at least one of the 5 compulsory exams. Variables in Columns (1) to (5) are from the student survey; variables in Columns (6) to (8) from administrative test score records. For outcomes in which the guardian reports usage and time use about the day before the survey, we control for day of the week fixed effects. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Impacts with no pooling at all

Table D.7: Impact on Light Use - All Treatment Arms

	(1) Lighting use yesterday guardians (hours)	(2) Lighting use yesterday students (hours)	(3) Lighting interruption last month	(4) Used solar light for homework	(5) Used tin lamp for homework	(6) Used kerosene lantern for homework
Free basic light	-0.156	0.452^{**}	-0.372^{***}	1.124^{***}	-0.968^{***}	-0.099^{***}
	(0.199)	(0.178)	(0.065)	(0.083)	(0.085)	(0.033)
High subsidy (USD 4)	-0.423^{**}	0.331	-0.398^{***}	1.023^{***}	-0.809^{***}	-0.093
	(0.168)	(0.198)	(0.071)	(0.067)	(0.083)	(0.055)
Low subsidy (USD 7)	-0.545	0.562	-0.666^{***}	0.999^{***}	-0.604^{***}	-0.144
	(0.477)	(0.594)	(0.200)	(0.179)	(0.182)	(0.158)
Market price (USD 9)	-1.106	0.530	-0.468^{**}	0.781^{***}	-0.780^{***}	-0.002
	(0.729)	(0.693)	(0.183)	(0.176)	(0.243)	(0.120)
Free larger light	-0.288	0.413^{***}	-0.413^{***}	1.004^{***}	-0.854^{***}	-0.115^{***}
	(0.199)	(0.144)	(0.050)	(0.067)	(0.063)	(0.035)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	3.136	3.234	0.472	0.000	0.867	0.128
Number of observations	1,313	1,203	1,286	1,051	1,051	1,051
R-squared	-0.07	-0.01	0.10	0.06	0.03	0.01
F-test for same effect	0.400	0.975	0.492	0.292	0.154	0.646

Notes: Treatment-on-the-treated estimates of having a working solar light on light use following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Columns (1) and (2) show the number of hours during which guardians and students, respectively, used any source of lighting. To measure time use in these variables, the respondents were asked about each time slot of the day. Column (3) shows lighting interruption due to running out of fuel or battery for any of their lighting devices in the past month, reported by the guardian. Columns (4) to (6) show whether the student relied on a solar light, a tin lamp, or a kerosene lantern as a main source of light for doing their homework, respectively. For outcomes in which the guardian reports usage and time use about the day before the survey, we control for day of the week fixed effects. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.8: Impact on Kerosene Use - All Treatment Arms

	(1) Number of kerosene-fueled lights used last month	(2) Number of tin lamps used last month	(3) Number of kerosene lanterns used last month	(4) Kerosene light used yesterday	(5) Kerosene purchased last month (liters)
Free basic light	-1.063^{***}	-0.943^{***}	-0.120^{*}	-0.295^{***}	-1.287^{***}
	(0.123)	(0.144)	(0.064)	(0.050)	(0.290)
High subsidy (USD 4)	-1.019^{***}	-0.911^{***}	-0.126^{*}	-0.217^{***}	-1.112^{**}
	(0.206)	(0.188)	(0.065)	(0.054)	(0.445)
Low subsidy (USD 7)	-1.075^{**}	-0.931^{**}	-0.144	-0.564^{***}	-0.157
	(0.483)	(0.434)	(0.293)	(0.170)	(1.185)
Market price (USD 9)	-0.858^{**}	-0.557	-0.301	-0.423^{***}	-0.663
	(0.390)	(0.389)	(0.190)	(0.116)	(0.679)
Free larger light	-0.782^{***}	-0.879^{***}	-0.106	-0.358^{***}	-1.220^{***}
	(0.252)	(0.123)	(0.066)	(0.048)	(0.219)
School FE	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes
Control complier mean	2.404	2.186	0.268	0.959	2.600
Number of observations	1,313	1,312	1,313	1,307	1,299
R-squared	0.08	0.11	-0.02	0.22	0.03
F-test for same effect	0.787	0.773	0.834	0.020	0.575

Notes: Treatment-on-the-treated estimates of having a working solar light on kerosene use following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Column (1) shows the number of kerosene lights the guardian used in the household in the past month. Column (2) refers to whether any household member used a kerosene lamp in the previous evening. Column (3) shows the change in liters of kerosene purchased in the past month at the household level. All variables are from the guardian survey. For outcomes in which the guardian reports usage and time use about the day before the survey, we control for day of the week fixed effects. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.9: Impact on Emissions - All Treatment Arms

	(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)
Free basic light	-78.22^{***}	$-2,895^{***}$	$-68,288^{***}$	-81.47^{***}
	(20.51)	(642)	(17,768)	(21.18)
High subsidy (USD 4)	-69.41^{**}	$-2,499^{**}$	$-60,523^{**}$	-72.20^{**}
	(26.69)	(1,012)	(23,293)	(27.79)
Low subsidy (USD 7)	-4.76	-383	$-4,360$	-5.23
	(85.91)	(2,682)	(74,399)	(88.69)
Market price (USD 9)	-27.78	$-2,076$	$-25,301$	-30.32
	(46.83)	(1,630)	(40,726)	(48.57)
Free larger light	-79.38^{***}	$-2,811^{***}$	$-69,170^{***}$	-82.51^{***}
	(13.53)	(512)	(11,783)	(14.05)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Control complier mean	164.51	5,748	143,276	170.89
Number of observations	1,291	1,291	1,291	1,291
R-squared	0.03	0.03	0.03	0.03
F-test for same effect	0.379	0.760	0.392	0.394

Notes: Treatment-on-the-treated estimates of having a working solar light on household emissions following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. The impact on emissions is calculated based on households' kerosene consumption, as reported in Column (3) of Table 4, and the type of kerosene lamp households use, as detailed in Subsection 2.1. As a result, these four columns are linearly dependent among each other. Column (1) shows black carbon, Column (2) CO_2 emissions, Column (3) CO_2-equivalents of the previous two columns combined, and Column (4) particulate matter ($PM_{2.5}$). Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.10: Impact on Expenditures - All Treatment Arms

	(1) Total expenditure	(2) Kerosene	(3) Phone charging	(4) Firewood	(5) Batteries	(6) Charcoal	(7) Electricity bill	(8) Other
Free basic light	-1.233^{***}	-0.722^{***}	0.419^{*}	-0.277^{*}	0.016	-0.190	-0.412	-0.067
	(0.377)	(0.182)	(0.234)	(0.153)	(0.073)	(0.241)	(0.300)	(0.152)
High subsidy (USD 4)	-1.240	-0.504^{**}	0.015	-0.508^{**}	0.060	0.163	-0.273	-0.193^{*}
	(0.761)	(0.176)	(0.162)	(0.218)	(0.103)	(0.576)	(0.296)	(0.098)
Low subsidy (USD 7)	-1.992	-0.087	-0.050	0.394	0.065	-0.017	-2.096^{**}	-0.201
	(1.712)	(0.588)	(0.437)	(0.771)	(0.195)	(0.686)	(0.966)	(0.237)
Market price (USD 9)	-3.431^{**}	-0.358	0.397	-0.503	0.349	-1.570^{***}	-1.523	-0.196
	(1.218)	(0.568)	(0.401)	(0.587)	(0.228)	(0.540)	(1.092)	(0.402)
Free larger light	-2.444^{***}	-0.919^{***}	-0.873^{***}	-0.095	0.133	-0.115	-0.432	-0.143
	(0.481)	(0.081)	(0.076)	(0.202)	(0.078)	(0.260)	(0.296)	(0.083)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	4.120	1.685	1.110	0.425	0.276	0.226	0.366	0.034
Number of observations	1,313	1,312	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	-0.03	0.04	-0.00	-0.01	-0.00	-0.03	-0.02	-0.02
F-test for same effect	0.186	0.151	0.000	0.173	0.247	0.021	0.302	0.275

Notes: Treatment-on-the-treated estimates of having a working solar light on households' monthly energy expenditures (in USD) following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Column (1) shows total energy expenditure, Columns (2) to (8) its components. Column (8) includes expenditures on candles, generator fuel, LPG, sawdust, dung/charcoal mixture, and other types of fuel. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.11: Impact on Health - All Treatment Arms

	Eyes		Respiratory	
	Guardians	Students	Guardians	Students
	(1)	(2)	(3)	(4)
Free basic light	-0.247^{**}	-0.251^{*}	-0.152	-0.221
	(0.117)	(0.121)	(0.125)	(0.137)
High subsidy (USD 4)	-0.313^{*}	-0.248^{*}	-0.138	-0.269
	(0.168)	(0.129)	(0.156)	(0.209)
Low subsidy (USD 7)	-0.142	-0.796^{*}	0.205	0.050
	(0.412)	(0.385)	(0.402)	(0.390)
Market price (USD 9)	-0.950^{**}	0.004	-0.270	0.197
	(0.368)	(0.613)	(0.421)	(0.487)
Free larger light	-0.225^{**}	-0.289^{**}	-0.126	-0.245
	(0.103)	(0.137)	(0.092)	(0.171)
School FE	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes
Number of observations	1,313	1,203	1,313	1,203
R-squared	-0.01	-0.01	-0.01	-0.01
F-test for same effect	0.305	0.435	0.821	0.672

Notes: Treatment-on-the-treated estimates of having a working solar light on health following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Columns (1) and (2) show an index of eye-related symptoms such as dryness, grittiness, redness, etc. based on Lee et al. (2002). Columns (3) and (4) show an index of respiratory symptoms such as shortness of breath, asthma, cough, etc. based on Bates et al. (2013) and The European Community Respiratory Health Survey II Steering Committee (2002). Effects are expressed in standard deviations. Higher values indicate more symptoms. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.12: Impact on Education - All Treatment Arms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Homework completion	Share homework after dark	Homework and personal studies (hours)	School (hours)	Sleep (hours)	Average score of 5 subjects	Average score KCPE	Participation in school exams in March 2016
Free basic light	0.148**	0.109**	0.347	0.729*	−0.466*	−0.094	−0.040	0.097*
	(0.056)	(0.048)	(0.215)	(0.396)	(0.238)	(0.146)	(0.284)	(0.053)
High subsidy (USD 4)	0.189***	0.165**	0.241	0.981*	−0.651*	0.044	0.317	−0.021
	(0.060)	(0.058)	(0.328)	(0.470)	(0.323)	(0.202)	(0.286)	(0.066)
Low subsidy (USD 7)	0.147	0.234	−0.212	−0.294	−0.676	−0.477	−1.574	−0.014
	(0.231)	(0.193)	(0.594)	(1.081)	(0.528)	(0.353)	(1.902)	(0.116)
Market price (USD 9)	0.074	−0.149	0.748	1.764	−0.801	0.138	2.060	0.196
	(0.251)	(0.137)	(0.875)	(1.329)	(0.626)	(0.417)	(2.829)	(0.172)
Free larger light	0.139***	0.096**	0.311	0.334	−0.416*	−0.031	0.007	0.014
	(0.047)	(0.037)	(0.225)	(0.288)	(0.203)	(0.101)	(0.251)	(0.038)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control complier mean	0.650	0.723	2.435	3.980	8.417	0.039	0.025	0.775
Number of observations	1,051	1,051	1,203	1,203	1,203	1,268	235	1,313
R-squared	-0.01	-0.02	-0.02	-0.01	-0.01	-0.02	-0.48	-0.01
F-test for same effect	0.895	0.061	0.794	0.257	0.946	0.443	0.368	0.454

Notes: Treatment-on-the-treated estimates of having a working solar light on educational outcomes following Equations (3) and (4). The sample of each regression includes households in the control group and the treatment arms offered the respective type of light. Column (1) shows whether the student was able to complete the homework in the past week. Column (2) shows the share of times the homework was completed after dark in the past week. Columns (3) to (5) show results for time use on the day before the endline interview (homework and personal studies, time spent in class, time spent sleeping). Column (6) shows the average final exam scores of the first term in 2016. When the score for a subject is missing, we use the corresponding score from the last term of 2015, when available. The probability of scores missing is balanced across treatment arms (see Appendix Table A.9). Column (7) contains the average score of graduating students who took the national KCPE exam. Column (8) indicates whether the student took at least one of the 5 compulsory exams. Variables in Columns (1) to (5) are from the student survey; variables in Columns (6) to (8) from administrative test score records. For outcomes in which the student reports usage and time use about the day before the survey, we control for day of the week fixed effects. Robust standard errors clustered at the household and school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E Impact Outcomes No Gender FEs

Impacts of main analysis

Table E.1: Impact on Light Use - Pooled - No Gender FE

	(1) Lighting use yesterday guardians (hours)	(2) Lighting use yesterday students (hours)	(3) Lighting interruption last month	(4) Used solar light for homework	(5) Used tin lamp for homework	(6) Used kerosene lantern for homework
Solar light	-0.201	0.362^{***}	-0.385^{***}	1.053^{***}	-0.888^{***}	-0.110^{***}
	(0.143)	(0.110)	(0.046)	(0.056)	(0.052)	(0.032)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	No	No	No	No	No	No
Control complier mean	3.127	3.268	0.470	0.000	0.862	0.127
Number of observations	1,313	1,203	1,286	1,051	1,051	1,051
R-squared	-0.02	-0.00	0.16	0.19	0.16	0.01

Notes: Treatment-on-the-treated estimates of having a working solar light on light use following Equations (3) and (4). Columns (1) and (2) show the number of hours during which guardians and students, respectively, used any source of lighting. To measure time use in these variables, the respondents were asked about each time slot of the day. Column (3) shows lighting interruption due to running out of fuel or battery for any of their lighting devices in the past month, reported by the guardian. Columns (4) to (6) show whether the student relied as a main source of light to do homework a solar light, a tin lamp, and a kerosene lantern, respectively. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.2: Impact on Kerosene Use - Pooled - No Gender FE

	(1) Number of kerosene-fueled lights used last month	(2) Number of tin lamps used last month	(3) Number of kerosene lanterns used last month	(4) Kerosene light used yesterday	(5) Kerosene purchased last month (liters)
Solar light	-0.926^{***}	-0.933^{***}	-0.110^{**}	-0.296^{***}	-1.331^{***}
	(0.159)	(0.097)	(0.042)	(0.034)	(0.215)
School FE	Yes	Yes	Yes	Yes	Yes
Respondent gender	No	No	No	No	No
Control complier mean	2.429	2.204	0.277	0.959	2.644
Number of observations	1,313	1,312	1,313	1,307	1,299
R-squared	0.08	0.13	-0.01	0.17	0.03

Notes: Treatment-on-the-treated estimates of having a working solar light on kerosene use following Equations (3) and (4). Column (1) shows the number of kerosene-fueled lights the guardian used in the household in the past month. Columns (2) and (3) show the number of tin lamps and kerosene lantern that the guardian used in the household in the past month. Column (1) is the sum of tin lamps, kerosene lanterns, and pressurized lamps. Column (4) refers to whether any household member used a kerosene-fueled light in the previous evening. Column (5) shows the change in liters of kerosene purchased in the past month at the household level. All variables are from the guardian survey. Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.3: Impact on Emissions - Pooled - No Gender FE

	(1)	(2)	(3)	(4)
	BC emissions (g/month)	CO_2 emissions (g/month)	CO_2-eq emissions (g/month)	$PM_{2.5}$ emissions (g/month)
Solar light	-84.66^{***}	$-3,002^{***}$	$-73,774^{***}$	-88.00^{***}
	(14.01)	(503)	(12,192)	(14.54)
School FE	Yes	Yes	Yes	Yes
Respondent gender	No	No	No	No
Control complier mean	166.72	5,845	145,222	173.22
Number of observations	1,291	1,291	1,291	1,291
R-squared	0.04	0.04	0.04	0.04

Notes: Treatment-on-the-treated estimates of having a working solar light on household emissions following Equations (3) and (4). The impact on emissions is calculated based on households' kerosene consumption, as reported in Column (5) of Table 4, and the type of kerosene lamp households use, as detailed in Subsection 2.1. The number of observations differ from those from Column (5) of Table 4 because we don't have information about the type of light used of 8 households. As a result, these four columns are linearly dependent among each other. Column (1) shows black carbon, Column (2) CO_2 emissions, Column (3) CO_2-equivalents of the previous two columns combined, and Column (4) particulate matter ($PM_{2.5}$). Robust standard errors clustered at the school level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.4: Impact on Energy Expenditures - Basic vs. Larger Light - No Gender FE

	(1) Total expenditure	(2) Kerosene	(3) Phone charging	(4) Firewood	(5) Batteries	(6) Charcoal	(7) Electricity bill	(8) Other
Basic light	−1.202***	−0.677***	0.270	−0.389**	0.004	−0.011	−0.289	−0.111
	(0.369)	(0.144)	(0.172)	(0.166)	(0.071)	(0.297)	(0.262)	(0.111)
Larger light	−2.540***	−0.953***	−0.881***	−0.113	0.107	−0.097	−0.447	−0.156*
	(0.494)	(0.077)	(0.075)	(0.214)	(0.083)	(0.257)	(0.306)	(0.086)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	No	No	No	No	No	No	No	No
Control complier mean	4.193	1.707	1.122	0.430	0.291	0.227	0.378	0.041
Number of observations	1,313	1,312	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	-0.01	0.05	-0.01	-0.01	0.00	-0.00	0.00	-0.01
F-test for same effect	0.022	0.096	0.000	0.152	0.316	0.799	0.557	0.543

Notes: Treatment-on-the-treated estimates of having a working solar light on households' monthly energy expenditures (in USD) by type of light. Each row results from a separate TSLS regression following Equations (3) and (4). The sample of each regression includes households in the control group and the respective treatment groups. Column (1) shows total energy expenditure, Columns (2) to (8) its components. Column (8) includes expenditures on candles, generator fuel, LPG, sawdust, dung/charcoal mixture, and other types of fuel. To conduct the F-test of whether the effect is the same across types of light, we use stacked regressions with robust standard errors clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.5: Impact on Health - Pooled - No Gender FE

	Eyes		Respiratory	
	Guardians (1)	Students (2)	Guardians (3)	Students (4)
Solar light	-0.222^{***}	-0.257^{**}	-0.133^{*}	-0.284^{*}
	(0.075)	(0.092)	(0.072)	(0.140)
School FE	Yes	Yes	Yes	Yes
Respondent gender	No	No	No	No
Number of observations	1,313	1,203	1,313	1,203
R-squared	0.00	-0.00	0.00	-0.01

Notes: Treatment-on-the-treated estimates of having a working solar light on health following Equations (3) and (4). Columns (1) and (2) show an index of eye-related symptoms such as dryness, grittiness, redness, etc. based on Lee et al. (2002). Columns (3) and (4) show an index of respiratory symptoms such as shortness of breath, asthma, cough, etc. based on Bates et al. (2013) and The European Community Respiratory Health Survey II Steering Committee (2002). Effects are expressed in standard deviations. Higher values indicate more symptoms. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

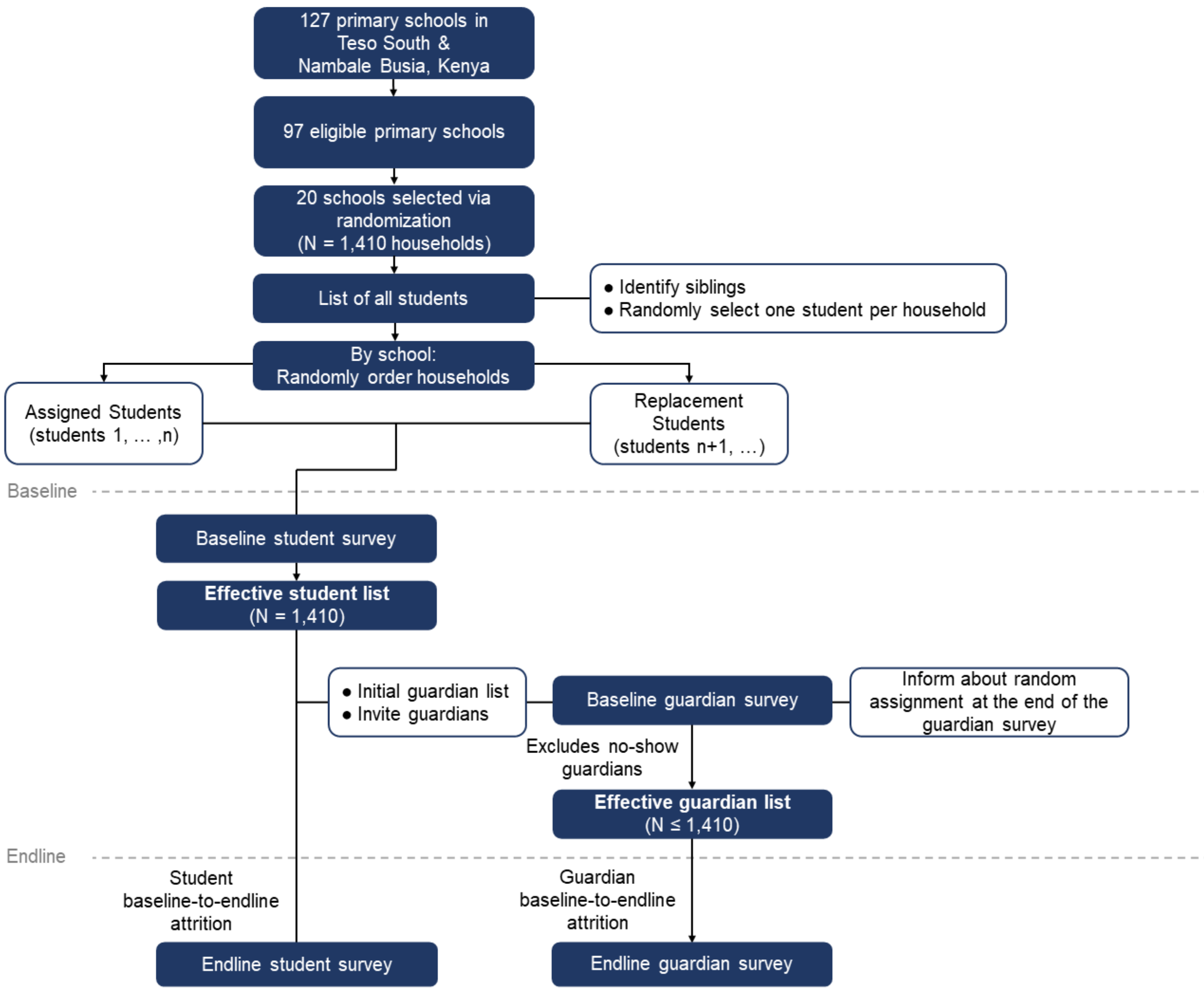
Table E.6: Impact on Education - Pooled- No Gender FE

	(1) Homework completion	(2) Share homework after dark	(3) Homework and personal studies (hours)	(4) School (hours)	(5) Sleep (hours)	(6) Average score of 5 subjects	(7) Average score KCPE	(8) Participation in school exams in March 2016
Solar light	0.158***	0.114***	0.325	0.545*	−0.439**	−0.032	−0.061	0.033
	(0.032)	(0.036)	(0.197)	(0.283)	(0.175)	(0.117)	(0.153)	(0.031)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent gender	No	No	No	No	No	No	No	No
Control complier mean	0.648	0.722	2.427	3.987	8.410	0.036	0.011	0.774
Number of observations	1,051	1,051	1,203	1,203	1,203	1,268	236	1,313
R-squared	-0.01	-0.01	-0.01	0.00	0.00	-0.00	0.00	0.00

Notes: Treatment-on-the-treated estimates of having a working solar light on educational outcomes following Equations (3) and (4). Column (1) shows whether the student was able to complete the homework in the past week. Column (2) shows the share of times the student did homework after dark in the past week. Columns (3) to (5) show results for time use on the day before the endline interview (homework and personal studies, time spent in class, time spent sleeping). Column (6) shows the average final exam scores of the first term in 2016. When the score for a subject is missing, we use the corresponding score from the last term of 2015, when available. The probability of scores missing is balanced across treatment arms (see Appendix Table A.9). Column (7) contains the average score of graduating students who took the national KCPE exam. Column (8) indicates whether the student took at least one of the 5 compulsory exams Variables in Columns (1) to (5) are from the student survey; variables in Columns (6) to (8) from administrative test score records. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

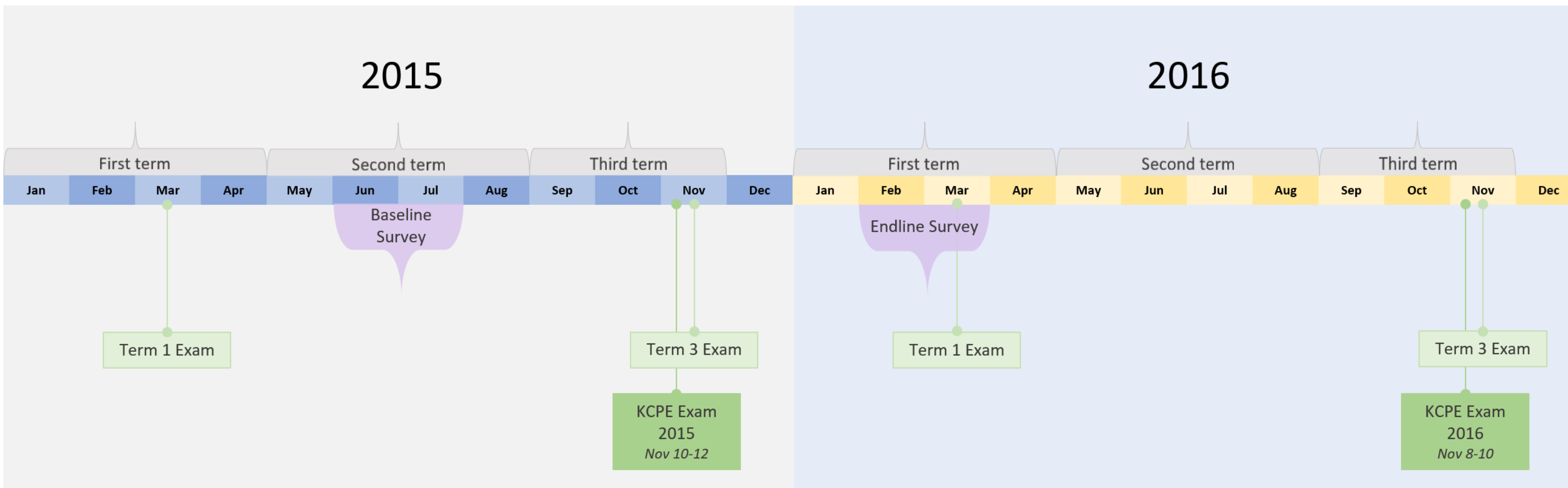
F Research Design

Figure F.1: Research Design and Survey Implementation



Notes: We received a list of 127 primary schools in the two subcounties of Teso South and Nambale Busua in 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 the class ranges 5-7. For households with siblings, we randomly selected one student per household. We then randomly ordered the student list, creating a list of initially assigned students and of replacement students. The treatment assignment would follow a specific pattern of the ordering of the student list. Randomization into treatments was conducted at the household level and stratified at the school level. We first interviewed the students at the school and missing students were replaced with students form the replacement list. We then invited their guardians for a baseline interview that took place several days after the interview. Households were informed about their treatment assignment at the end of the guardian baseline interview.

Figure F.2: Timeline of the Experiment



Notes: Baseline surveys were conducted in June–July 2015, which was 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 10th to 12th November 2015 (Kenya National Examinations Council, 2015) and from 8th to 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 F.1: Sampled Households by School and 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

F.1 Pre-Baseline

Household list: Before starting the baseline, the household list was prepared based on a list of students in classes 5-7 from the selected schools. Schools were selected based on a list of 127 schools received from the Ministry of Education. We removed urban schools as these areas often have better access to electricity. From the rural schools, four did not contain information on the number of students and were thus excluded. Based on the pool of remaining schools, we randomly selected 30 schools in each sub county. Consequently, we removed boarding schools, unisex schools, schools for children with special needs, those with less than 200 students across all grades[46], those too far away to be reached within one day from the field office, and five schools that were already part of other projects. Head teachers were invited to a meeting that explained the solar lights used in the study. Prior to the meeting, we randomly ordered the schools and the first ten schools in each subcounty were asked to participate in the study at the end of the meeting. Four head teachers were not present at the meeting and the respective schools were replaced with the subsequent schools on the randomly ordered list. The schools were visited to identify siblings.[47] In case of students coming from the same household, one student of that household was randomly selected. This gave a final list of one student per household in classes 5-7 for each school.

Randomization: Based on the final household list, the treatment was randomly assigned. This was done by randomly ordering the households within each school. The treatment was then assigned based on a specific pattern. In particular, the first 40 students were assigned to the control and free solar light group in alternating order (starting with the control group). Among those receiving a free solar light, treatment alternated between the basic solar light and the mobile-charging (larger solar light) option (starting with the basic option). Voucher treatments were given to those households ranked 41 or higher with an alternating pattern between voucher-400, voucher-700 and voucher-900. More students than required were randomly ordered to create a list of back-up students. Hence, the order of the back-up student list was also random. For the 13.4% of cases in which students initially selected for the study did not attend school on the day of survey, we then randomly selected replacement students. The share of replacement students is balanced across treatment arms. Note that the treatments were assigned in advance of the baseline interviews.

There are 2 schools in which the randomization posed additional challenges.

- Nambale Sub-County
  In Sango school, the number of households whose children were in class 5, 6 and 7 was small; Thus, we only allocated households to the free group and/or the control group (i.e. we only sampled 40 students total in that school as shown in Appendix Table F.1). At that point we decided to increase the number of vouchers distributed in the remaining schools in Nambale: we increased the number of treatment households to

[46] Two schools had less than 70 students in grade 5-7, even though overall more than 200 students were enrolled. These are likely to be newer schools, such that most students were enrolled in younger grades

[47] During implementation, the surveyors still identified cases of siblings among the randomized student list. In these cases, only one of the siblings was removed and the other siblings replaced with a student from the back-up list.

80 in two of the largest remaining schools (Sianda, and Khayo) and increased to 75 treatment households Opeduru (relatively medium size school). For Mwangaza, the relatively smaller school, we didn't make any changes, allocating only 70 treatment households.

- Teso South Sub County
  In Aburi school, there were only 50 students that complied with the selection criteria, thus, only 10 vouchers were given away (4 of high subsidy, 3 of low subsidy, and 3 at the market price). Given this change, we increased the sample size in all other schools of this sub county to 75.

The process to communicate the treatment offers to participants was as follows. Surveyors gave respondents a "lucky number" to participate in a lottery, which was similar to other lottery games common in Kenya.[48] Respondents then sent a text message with the lucky number to participate in the lottery and immediately received a text message back, announcing whether they won a free solar light, had the opportunity to purchase a light at a given price during the following weeks, or did not win anything. As similar types of text-message games are common in Kenya, this process was easy to understand for participants and made it intuitively clear that the allocation was random.[49]

Student invitation to baseline: The baseline student survey was conducted at school. Thus, students were encouraged to be present on the day of the survey. The students who were supposed to be interviewed (i.e., those not on the back-up list) were specifically asked to be present. Students on the back-up list were not asked specifically to be present that day. While head teachers may have seen the list of randomized students before the baseline interviews were conducted, this list did not include the treatment assigned. Similarly, the assignment rule based on random student ID was unknown to the head teachers.

F.2 Baseline Student Survey

General organisation: Interviews were scheduled on a specific day for each school. There were three surveyor teams who were assigned to different schools respectively. Hence, students at three different schools were interviewed each day. A team interviewed students from all treatment groups, that is, the team was not split up between the survey versions.

Student selection: For each school, there were two randomly generated lists: (i) assigned students and (ii) replacement students. Students present from the assigned list were interviewed and, generally, the order of the randomized list was followed. In this case, the order is free and control groups first, followed by the voucher group. If a student was not present for the interview, the next available student from the replacement list was interviewed

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

[49] We tested this process in several pilots, discussed it with participants, and made sure the lottery was well understood.

instead. This replacement student then took over the five-digit ID of the initial student.

Student interview: Students were interviewed in the school. Depending on their pre-assigned treatment, they were interviewed using the long or the short (voucher) interview version. Students were not told about the treatment assignment at any point of the baseline interview. The student was also asked about their guardian (e.g., their name and phone number).

Final student sample: Since missing students from the assignment list were replaced with other students, the final student sample should include 1,410 students by design.

F.3 Baseline Guardian Survey

Guardian invitation: Guardians were only involved and invited after the student interview. Thus, the final student sample also determines the guardian sample. Students who participated in the baseline interview were asked to invite their guardian to the interview on a specific day and time. The students received paper slips with the invitation, including a note that they would receive a participation gift and would be reimbursed for travel costs (up to a certain ceiling). The survey team reminded the guardian of the interview if the phone number was available, but often the phone number provided by the student was wrong.

Guardian sample: In principle, students were asked about the guardian name, but this list had to be updated when the guardian who showed up differed from the one the student listed.[50] Note that guardians of students on the initial assignment list who were then absent at school (and thus dropped out of the sample) were not invited.

Guardian interview: The interviews were conducted at the school. In general, interviews followed an order similar to the checklist. That is, the free and control group were interviewed first, followed by the voucher groups. Guardians in the free treatment groups, received their solar light directly at the end of the interviews[51]. Participants in the voucher group received the voucher instead, which could be redeemed at a later day. If the guardian did not show up, the survey team tried to find the guardians.

Redemption and distribution of solar lights in the voucher group: For the guardians whose households were allocated a voucher, they were given dates and times upon which they could come back to the school to purchase the lamp (it was not available for purchase on that day). Granting a certain amount of time for people to redeem the voucher is the usual way SunnyMoney operates. Furthermore, this period of grace (?) allows people

[50]For instance, the student may have mentioned one of her parents, but the other parent showed up at the interview. All guardians were asked if they stay in the same house as the student for at least four nights a week.

[51]In the case of the free light households, if it was an in-home interview, the lamp was brought along by the field agent

to save enough money to purchase the solar light.[52]
In some cases, the head teachers collected the orders from the guardians as well as their money and vouchers, and purchased the solar lights from *SunnyMoney* on behalf of the guardians. The collection of the money and vouchers took place in several rounds. In other cases, some participants went to *SunnyMoney* directly.

Missing guardians: If the guardian did not participate in the endline, the guardian did not receive their treatment. At least in the data, there are no cases where a missing baseline-guardian was interviewed at endline. However, students were still interviewed even if their guardian did not participate in the baseline.

F.4 Endline Student Survey

General organisation: Like for the baseline, the student interview was conducted at the school directly. The head teacher was notified to inform the students to be present at school that day. When the student was not present at school that day, the surveyors tried to track the students.[53]

F.5 Endline Guardian Survey

General organisation: The endline guardian interview was conducted at the guardian's home. Instead of organizing the interviews by school or treatment arm, the interviews were planned according to geographic proximity. Hence, the checklist was reorganized by school. There are usually a number of villages per school. The survey team tried to book appointments with the guardians and notified them before coming. For guardians without phone number, the survey team went through the village elder.

[52] In fact, in an RCT of Dupas (2009) in Kenya, the author found that the demand for bednets fell less sharply with price when the households were given more time to raise money to purchase this item.

[53] Some students were found at their house, others moved to another school by then. Depending on their availability, an appointment was booked with them.

G Methodology for CO_2 Abatement Cost and Impact on National Emissions Calculations

Table G.1: Assumptions and Sources for CO_2−eq Calculations

	Unit	Amount	Source
Total GHG emissions	Mt CO_2-eq	74.24	Climate Watch (2022)
Energy GHG emissions	Mt CO_2-eq	18.59	Climate Watch (2022)
Using kerosene	%	35.0	KIHBS (2018)
of which using tin lamps	%	55.1	KIHBS (2018)
of which using kerosene lanterns	%	44.9	KIHBS (2018)
Black carbon to CO_2-eq conversion factors			
SFP Eastern Africa 100 years	SFP	836	Bond et al. (2011)
- lower bound	SFP	371	Bond et al. (2011)
- upper bound	SFP	1300	Bond et al. (2011)
GWP 100 years	GWP	900	Bond et al. (2013)
- lower bound	GWP	120	Bond et al. (2013)
- upper bound	GWP	1800	Bond et al. (2013)
Number of households in Kenya	#	11,415,000	KIHBS (2018)
CO_2-eq discount rate	%	2	Rennert et al. (2022)
Embedded energy in solar light production	MJ	100	Alstone et al. (2014)
Emissions from required energy for production	g(CO_2-eq)/kWh	1700	Dones et al. (2004)
Density of kerosene	kg/l	0.8	TotalEnergies (2022)

Notes: Total GHG emissions refers to Kenya's total GHG emissions including land use change and forestry (LUCF) in 2015. Energy GHG emissions refers to Kenya's total emissions in the energy sector in 2015. Percentage using kerosene and number of households in Kenya are based on survey data from Kenya from 2015/2016. Specific Forcing Pulse (SFP) is a concept introduced by Bond et al. (2011) measuring the energy added to the Earth-Atmosphere by one gram of chemical species emitted in a particular region. More information on calculations is to be found in Appendix sections G.1 and G.2.

G.1 CO_2 Abatement Cost

The following outlines the methodology to estimate the CO_2 abatement cost for the solar light intervention. That is, we attempt to estimate the cost of averting one ton of CO_2 in USD by distributing solar lights.

Parameters

The following parameters are used for our estimation.

Name	Description
$breakage$	Average monthly breakage rate of solar lamps
$TakeupRate_t$	Percentage of participants who redeemed their vouchers or picked up their lamp, depending on their treatment t
$CO_2Production$	CO_2 emitted during production of a solar lamp
$cost\_lamp$	Cost of a solar lamp

Effect of Solar Light Ownership on CO_2 Emissions per Household

First, we estimate the average reduction in CO_2 emissions per household using an instrumental variable regression and the two-stage least square estimator. We use each treatment arm as a separate instrument for the first stage, and estimate the treatment-on-the-treated (TOT) effects in the second stage jointly across treatments. We do this for different samples as outlined below.

The IV estimation is represented by the following regressions:

$$solar\_works_{ij} = \sum_{k \in K} a_k T_{ik} + \zeta_i + \lambda_j + u_{ij} \tag{5}$$

$$CO2\_eq\_wins_{ij} = b\ \widehat{solar\_works}_{ij} + \zeta_i + \lambda_j + \epsilon_{ij} \tag{6}$$

where T_{ik} is a dummy for assignment of household i to treatment group k, $solar\_works_{ij}$ a dummy equal to 1 when household i owns a working solar light and ζ is the respondent gender dummy. λ represents school fixed effects, and ϵ is an error term. $CO2\_eq\_wins$ proxies the amount of kg of CO_2 equivalents emitted by a household per month (at endline, winsorized at top 1%).[54] The point estimate b in Equation (6) is the (local) average treatment effect of owning a working solar lights on CO_2 emissions for households whose light ownership is induced by the treatment.

We implement this estimation for three samples respectively:

- Free basic light: free-basic, voucher400, voucher700, voucher900
- Free larger light (*mobile*): free-mobile
- Pooling both types of light (*pool*): free-basic, voucher400, voucher700, voucher900, free-mobile

Present Value of Annual CO_2 Reduction per Household

To provide an unbiased estimate of the intervention's impact in a real-world scenario, we need to take into account non-compliance and the solar lamp's breakage rate. $\hat{b}$ represents the impact on compliers, but there were participants who never redeemed their voucher and others whose lamp stopped working throughout the intervention. Accounting for these aspects, the monthly CO_2 reduction per household (in kg) amounts to:

$$Monthly\ CO_2\ Reduction = TakeupRate_t * \hat{b} * (1 - breakage) \tag{7}$$

For $CO_2 Production$ we assume that there are 47.2 kg of CO_2 embedded in the solar light from production. This estimate is primarily based on two sources: The embodied energy required is based on estimates from Alstone et al. (2014) and encompasses the primary energy required for manufacturing, transporting, and installing the solar lamp. According to their estimation, the embodied energy for manufacturing solar LED lighting systems ranges from

[54] $CO2\_eq_i = (836 \times F_{BC,light\_type} + F_{CO_2,light\_type}) \times ker\_kg_i = (836 \times F_{BC,light\_type} + F_{CO_2,light\_type}) \times 0.8 \times ker\_month\_l_i$, where $F_{X,light\_type}$ are the conversion factors for black carbon and carbon dioxide presented in Subsection 2.1.

25 to 500 MJ. While they do not assess the exact same lights as the ones in this study, we use the estimates of the primary energy requirements that are most comparable at 100MJ, which translates to 27.78 kWh, as 1 MJ = 0.277778 kwh. Furthermore, we assume that approximately 1700g CO_2-equivalents are emitted per kWh of energy used to produce the solar lights, based on Dones et al. (2004). Their estimates range from approximately 850 to approximately 1700 g(CO_2-equivalents)/kWh in a comparison of five different studies. The upper estimate of the range is from a coal chain in the Shandong Province in China which Dones et al. (2004) obtained from Dones et al. (2003). We chose this rather conservative estimate of approximately 1700g/kWh which assumes that all parts of the lights are produced with coal energy in inefficient power plants in China.

Using these two values, we estimate 47.2 kg of CO_2 embedded in the solar lights from production: 27.78*1700=47'236g = 47.2kg CO_2.

$$CO_2Production = embedded\,energy\,required\,(kWh)\;*CO_2\,emitted\,(g/kWh) \tag{8}$$

We then calculate the total reduction (in kg of CO_2) and deduct the CO_2 emission embedded in the production of the solar light ($CO2\_production$).[55] However, we only deduct the CO_2 emissions embedded in the production of those lights that were actually purchased for the intervention. We therefore multiply the CO_2 emissions with the respective take-up rate of each treatment arm. We assume an infinite time horizon taking into account the monthly breakage rate of the solar lamps as shown in equation 7. Using the formula for infinite sums we get:

$$\begin{aligned} &Total\,Net\,CO_2\,Reduction \\ &\qquad = [TakeupRate_t * \hat{b} * \frac{1}{breakage}] - CO_2Production * TakeupRate_t \end{aligned} \tag{9}$$

Cost per Ton of CO_2 Averted

We divide the initial cost of a solar light (in USD) by the total net CO_2 reduction (in tons) to arrive at the cost per ton of CO_2:

$$Cost\,per\,ton\,of\,CO_2 = \frac{cost\_lamp_t}{\frac{Total\,Net\,CO_2\,Reduction}{1000}} \tag{10}$$

For the treatment arm who received the basic light for free, we use the market price of USD 9 per lamp. For the free larger light, we use the market price of USD 24 per free larger light. We assume that this market price already includes all administrative and logistical cost that occur during the distribution of the solar lamps. For the voucher treatments, we subtract the respective subsidy from the market price but add an additional fixed cost. This additional cost arises since the implementing organization needs to visit the schools one additional time (compared to free lamp distribution), once to distribute the vouchers and once to sell the lamps. This cost amounts to *Average Daily Wage of NGO Employee * 1 Day per School **

[55] The estimate for the embedded emissions is based on Alstone et al. (2014). We assume that the same amount of CO_2 is emitted during the production of either type of light.

*20 Schools = 12 USD * 1 * 20 = 240 USD*. This fixed cost is then divided by the number of participants (n=1400) to represent the fixed cost per lamp. This cost estimate is likely to be a lower bound for the actual fixed costs since additional administrative, transport or logistical cost might arise when distributing the solar lamps via voucher.

G.2 CO_2 Reduction at the National Level

The objective is to estimate by how much national CO_2 emissions would be reduced if every household using a kerosene-fueled light in Kenya received a solar light − ceteris paribus.

Effect of Solar Light Ownership on Households' Kerosene Usage

Analogous to the previous section and Equations (5) and (6), we regress $ker\_month\_l\_wins$, the number of litres of kerosene purchased by a household per month (at endline, winsorized), on the instrumented $\widehat{solar\_works}$:

$$ker\_month\_l\_wins = b\ \widehat{solar\_works} + \zeta + \lambda + \epsilon \tag{11}$$

Originally, this analysis was performed for two disjoint subsets of the sample: First, we restricted the sample to households who previously only used tin lamps ($tin\_only == 1$), yielding a point estimate $\hat{b}_{tin}$. Second, we restricted the sample to households who previously only used large kerosene lanterns ($large\_ker\_only == 1$), producing a point estimate $\hat{b}_{large}$. This was done to account for the fact that the different light types use up different amounts of kerosene, and therefore generate different levels of carbon emissions. However, this specification proves too restrictive when implementing the estimations by type of light across all the treatment groups (i.e., the free basic light vs. the free larger light subset). More precisely, there are only 6 observations where $large\_ker\_only == 1$ in the free larger treatment group, and only 19 in the free basic group. For this reason, the current implementation relaxes the sample restrictions and performs the analysis for only one sample, including households who use tin lamps, large kerosene lamps, or both. In consequence, estimation for each subsample yields $\hat{b}_t$, which can be considered as an average reduction in kerosene purchases for households using different kerosene-fueled lights.

Extrapolating Results to the National Level

We first calculate how much CO_2 each lamp produces per kg of fuel. We assume that each Kenyan household that currently uses a kerosene-fuelled lamp receives a solar light and can thus realise the fuel savings $\hat{b}_t$ estimated in Equation (11). We finally calculate the effect of a nation-wide scale-up as a weighted average.

In order to estimate how many kg of CO_2 each lamp produces per kg of burnt fuel, we take both the direct CO_2 emission and the black carbon (BC) emission converted to CO_2 equivalents into account. The emissions by fuel type (in g of emissions per kg of fuel) are taken from Lam et al. (2012b). The conversion factor (CF) of 836 to translate BC into CO_2 equivalents is derived from Bond et al. (2011)'s SFP values. For Eastern Africa, the authors estimate an SFP of 1.17 ±0.65. For a 100 year time horizon, SFP is divided by $1.4*10^{-3}$ GJ

g^{-1}. We calculate the CF as:

$$CF_{SFP\,100-year} = \frac{1.17}{1.4 * 10^{-3}} = 835.71 \approx 836 \tag{12}$$

For the upper bound:

$$CF_{SFP\,upper\,100-year} = \frac{1.82}{1.4 * 10^{-3}} = 1300 \tag{13}$$

And for the lower bound:

$$CF_{SFP\,lower\,100-year} = \frac{0.52}{1.4 * 10^{-3}} = 371.42 \approx 371 \tag{14}$$

We then estimate the kg of of CO_2 produced per kerosene lamp through:

$$CO2_{lamp\,type} = \frac{836 * BC\ Emissions + Direct\ CO_2\ Emissions}{1000} \tag{15}$$

Using data from Kenya's national statistics, we find the share of households who predominantly use tin lamps ($\%_{tin}$) or who predominantly use large kerosene lamps ($\%_{large}$) as their main lighting source, expressed as percentages of all households who use kerosene lamps.[56] The estimated reduction per household (in kg of CO_2) is then calculated as follows:

$$CO_2\ Reduction\ p\ HH\ (National) = \hat{b}_{sample} * (\%_{tin} * CO2_{tin} + \%_{large} * CO2_{large}) \tag{16}$$

As in the previous section, we then account for lamp breakage per month and calculate the total reduction as follows:

$$\begin{aligned} &Total\ Net\ Reduction\ in\ CO_2\ p\ HH\ (National) \\ &\quad = [TakeupRate_t * CO_2\ Reduction\ p\ HH\ (National) * \frac{1}{breakage}] \\ &\qquad - (CO2\_Production * TakeupRate_t) \end{aligned} \tag{17}$$

Again, the average cost per ton of CO_2 is calculated as follows:

$$Cost\ per\ ton\ of\ CO_2\ p\ HH\ (National) = \frac{cost\_lamp_t}{\frac{Total\ net\ reduction\ in\ CO_2\ p\ HH\ (National)}{1000}} \tag{18}$$

Projections as a Percentage of Kenya's 2014 National Emissions

In order to estimate the total yearly CO_2 reduction[57] if the programme were scaled up nationally, we find the total number of households in Kenya (N) and the share of households who use kerosene lamps as their main lighting source ($\%_{kerosene}$) in Kenya's national statistics.

[56] That is, we define $\%_{tin} = \frac{Households\ in\ Kenya\ that\ use\ tin\ lamps}{Households\ in\ Kenya\ that\ use\ tin\ or\ large\ kerosene\ lamps}$.

[57] We are only looking at the gross yearly reduction here, not taking into account the CO_2 emissions embedded in the solar lights.

We assume that all households who mainly use kerosene lamps realize yearly savings as follows:

$$\begin{aligned} &CO_2\,Reduction\,per\,HH\,(National,\,Year\,1) \\ &\qquad = \sum_{m=1}^{12} CO_2\,Reduction\,per\,HH\,(National) * (1 - breakage)^m \end{aligned} \tag{19}$$

We then divide by 10^9 in order to convert our result to megatons:

$$\begin{aligned} &Total\,CO_2\,Reduced\,in\,1\,Year\,(in\,Mt) \\ &\qquad = \frac{N * \%_{kerosene} * CO_2\,Reduction\,per\,HH\,(National,\,Year\,1)}{10^9} \end{aligned} \tag{20}$$

We divide this estimate by the total emissions for Kenya in 2019 (Climate Watch, 2022) in order to arrive at the share of total emissions that could be reduced through a nation-wide roll-out:

$$Share\,of\,total\,emissions\,in\,2019 = \frac{Total\,CO_2\,Reduced\,in\,1\,Year\,(in\,Mt)}{Total\,emissions\,in\,2019\,(in\,Mt)} * 100\% \tag{21}$$

The share of energy emissions is calculated analogously.

H Methodology for Sensor Data Analysis

Sensor technology was manually welded post-production to some of the lamps circuits by the investigators with the intention of measuring solar light usage through a different channel than only surveys. The installed sensors were very simple, essentially only detecting and storing status changes of lamp, i.e. the time when it got turned on or off respectively. This information was stored within the sensor and could be downloaded by the Field Officers (FOs) through a tailor-made phone app. Over different sessions the FOs distributed the different lamps (with or without welded sensor) and also over different sessions they collected the sensor data from all sensor-equipped lamps. This implies that there is no natural observation window for this data, and we will thus need to pick a 7-month window starting late enough such that all households already have the lamp and, at the same time, closing early enough such that all the data is collected. The use of sensors in this RCT is discussed in detail in another paper (see Rom et al., 2020).

We start from the database of raw events downloaded from the FOs. We first fix a few isolated problems for some of the sensors.[58] At this point we have 315 unique sensors and 884,217 event logs. Now we drop all the observations that are not consistent with the on/off natural pattern (an event should be off if the previous was on and the other way around, as you can't turn off a light that is already off). I.e., if there are two or more consecutive on events we delete the first one(s) whereas if there are two or more consecutive off events we delete the last one(s). This is intended to never split a consecutive on/off pattern and to not arbitrarily inflate recorded usage. With this operation we end up dropping 6,385 events. We then further drop all the events which are the first for a given sensor and are not an on-event, or the last for a given sensor and are not an off-event. There are 8 such events. At this point we have 877,824 event logs and still 315 unique sensors.

Now we convert timestamps to Kenyan time as original logs are recorded in UTC (corresponding to the GMT+0 timezone) whereas Kenya is on GMT+3 all year round. We realise that 43,452 events (just under 5% of the database at this point) have a timestamp dating to the year 1970.[59] After thoroughly exploring these erroneous observations we realise that the best approach is to simply discard them all. Even if we wanted to fix these observations by shifting them to the correct point in time we would not know what the correct point is. We cannot know whether the 1970 observations of a given sensor should come before the first non-1970 recorded log or after the last non-1970 recorded log. We tested both approaches and realized that the correct solution is a mix of these two as both separate approaches yield dates that are inconsistent with the time frame of the study for some of the sensors. Finding the correct shift for each sensor is thus impossible without making baseless assumptions, in particular considering that both situations could co-exist for any given sensor. Thus, after getting rid of them, we now have 267 unique sensors and 834,372 event logs. Through this operations we lost many sensors but the vast majority of them only had a couple of logged

[58] There were 61 observations that had to be encoded from a numeric value to "on" (30 observations), and "off" (31 observations), and there were 5 observations that seemed superfluous and erroneous logs which we thus dropped.

[59] This is not a coincidence. Current time on UNIX systems is represented as the number of milliseconds from January 1^{st}, 1970 00:00:00. Most electronic applications will thus start counting time from that timestamp onwards unless a custom date and time is set. Most importantly, they could also revert back to that time if they get reset for some reason as, e.g., malfunctioning, battery death (Epoch Converter, 2023).

events, all in 1970.

At this point we reshape the dataset to have each on event and its correspondent off event on the same row, and thus easily calculate the duration of usage. The number of observations halves to 417,186 and we will now talk about usages (i.e. time span between on and off events) rather than events. We now drop all the usages with length of 0 minutes[60], since they serve no purpose for us, as when adding up minutes they will not count towards the total. Now we have 260 unique sensors and 339,847 usages. Then, we drop some usage-outliers (86 cases) by setting the cutoff at 24 hours of uninterrupted usage as we fear they might unfaithfully skew our results as well as a few time-outliers that happen before May 25th 2015 (Monday) and after May 8th 2016 (Sunday), enabling us to have a clean 50-week-long period of Monday-Sunday weeks where at least one sensor is active in each week. With this operation we lose 1 sensor and 6 usages. Finally, we split usages that span over two different days (i.e. go over midnight) such as to attribute the light usage to the correct day. This happens in 7,695 cases.[61]. At the end of this whole process, we now count 259 unique sensors and 347,336 usages.

Unfortunately, the current time frame is not appropriate due to the fact that lights were distributed from the end of May 2015 until the beginning of August 2015, meaning that considering a time before everybody has gotten their light would imply biased results. On the other hand, the final data collection from the sensors did not happen for everybody on the same date as it happened between the end of March 2016 and the beginning of May 2016. Thus, we need to set a 7-month window that is not affected by these issues. We selected this window to be from August 17th (Monday) 2015 to March 20th 2016 (Sunday). The reason for this is that by August 17th all the lamps were already distributed and we know that the first sensor data collection happened after March 20th. This is a quite-perfect 7-month period that entails 31 full Monday-Sunday weeks encompassing 228 unique sensors and 256,127 usages. This is the sample that we use to construct Figure 2.

At this point we construct datasets at the week level where we sum up the number of hours the lights are on over the whole week as well as counting the number of days per week where the light is used for at least 1 minute. To construct Figure 2 we need a few more steps. First, we divide the number of hours by 7 to get the average number of hours per day. Then, we aggregate across sensors in two different ways. The *conditional on sensor still active* variables are constructed such that the weekly average across the sensors is only computed considering the sensors that are still active. We define sensors as active if they are either turned on in the given week or were turned on at least once before in any prior week and are turned on again in any subsequent week. This is done to exclude the effects of sensors or lights breaking down over time, or even just that some household might not be using the lamp at all, while considering sensors as active if they are still being used by the household, even if they are periodically not used. In most cases, when a sensor does

[60]Unfortunately the sensor only store timestamps up until minute precision, such that seconds were not stored. For this reason, if a lamp was used between for example 8:27:00 and 8:27:59 it will results as if it was used for 0 minutes even though it was used for almost an entire minute. On the other hand, a lamp being used from 8:58:59 until 8:59:00 will be recorded as being used for one minute even though it was used for 2 seconds at most.

[61]A small share of them go just up until midnight meaning that once we "split" them they do not end up being two separate events because the one of the following day, being of zero minutes length, gets dropped.

not record activity in a given week, the sensor also records no further activity until the end of our observation period, with few exceptions. In the *unconditional* variables we instead consider all these effects by always taking average across all 228 unique sensors that we have at this point. Technically, we do this by enforcing a balanced panel at the sensor-week level thus introducing null observations before averaging across sensors. It is natural to expect unconditional outcomes to decrease over time as lights and sensors definitely break (in particular it seems that lights where sensors were installed tend to break more often). If we were to see a constant or even positive trend for these variables it would automatically imply that the conditional usage of the lights increases over time and thus (over)compensates the breakage rate of the lights/sensors.

I Survey Questions Used for Indexes

Questions for Index of Respiratory Symptoms

Based on Bates et al. (2013) we asked the following 5 questions (yes/no answers). We aggregated all the symptoms and created a score ranging from 0-5.

- In the last 3 months have you ever had wheezing or whistling in your chest?
- In the last 3 months have you ever woken up with a feeling of tightness in your chest?
- In the last 3 months have you ever experienced an attack of shortness of breath that came on during the day when you were at rest?
- In the last 3 months have you ever been woken up at night by an attack of shortness of breath?
- In the last 3 months have you ever been woken up at night by an attack of coughing?

Questions for Index of Eyes-Related Symptoms

As for the questions about eyes-related symptoms we asked the following 5 questions (Options: every day, most days, some days, rarely, never, coded as dummy, where 1 = all choices except "never"). We aggregated all the symptoms and created a score ranging from 0-5.

Do you experience any of the following and if so, how frequently?

- a feeling of dryness in your eyes?
- a feeling of grittiness (having sand) in your eyes?
- a burning feeling in your eyes?
- redness in your eyes?
- crusting with yellow discharge in your eyes?
- sticking together of your eyelids when you wake up in the morning?

J Script with Information about Solar Light

Now I will show you a solar light called SUN KING ECO and we will give you the opportunity to play a game where you can win this product or a similar one. Show the product:

- The lantern comes with a separate panel that you can put outside to charge in the sun.
- There are three different modes to use this lantern (SHOW THEM). In the first least bright you can use it for 30 hours, in the middle one for 6 and in the brightest one for 4 hours.
- The product comes with a warranty of 2 years and a battery that can last up to 5 years.

K Pictures of Lights

Figure K.1: Kerosene Lantern

Tin Lamp

Kerosene Lantern

Figure K.2: Solar Lights

Free Basic Solar Light

Brand name: Sun King Eco

Free Larger Solar Light

Brand name: Sun King Mobile

L Literature Review

Table L.1: Health and Education Impacts - Literature Review

Study	**Country**	**Intervention Type**	**Outcome Type**	**Health Impacts**				**Education Impacts**			
				Eye Symptoms		*Respiratory Symptoms*		*Homework (hours)*	*Study time (hours)*	*School (hours)*	*Test score*
				Student	Guardian	Student	Guardian				
Furukawa (2017)	Uganda	Distribution of solar desk lamps with market price of 10 USD by 2017 to 5th to 7th grade students.	Binary outcome variables, equal 1 if symptoms exist at any level (mild, moderate, serious), and 0 if no symptoms.	Eye irritation: -0.11***	-	Cough: -0.06 Diff Breath: -0.07 Chest pain: -0.11** Sore throat: -0.06	-	-	-	-	-
Kudo et al. (2019b)	Bangladesh	**Treatment A:** 3 light solar products (164 lumens) at total cost of $ 63.5 USD by 2018. **Treatment B:** 1 solar light product (110 lumens) at total cost of around $ 40 USD. Population was 4th to 8th grade students.	Binary outcome variables, equal 1 if the student reporting having the symptom at endline.	**Treatment A:** Any visible burn: -0.045** Eye redness: -0.143** Eye irritation: -0.137** Teary eyes: -0.020 Dimness of vision: 0.006 **Treatment B:** Any visible burn: -0.001 Eye redness: -0.141*** Eye irritation: -0.103* Teary eyes: -0.034 Dimness of vision: 0.002	-	**Treatment A:** Cough: 0.008 Sore throat: 0.000 Snivel: -0.039 Phlegm: -0.005 **Treatment B:** Cough: -0.031 Sore throat: -0.009 Snivel: -0.043 Phlegm: -0.003	-	-	-	-	-
Grimm et al. (2017)	Rwanda	Provision of Pico-PV kits including a 1 Watt panel, a rechareable 4-LED-diodes lamp (40 lumen max.) + installed battery, a mobile phone charger, a radio + charger, and a back-up battery package.	Outcomes measured as share of household members (in percent) suffering from symptoms.	**Male** 6-11 y.o.: -3.00 12-17 y.o.: 1.00 **Female** 6-11 y.o.: 5.00 12-17 y.o.: 8.00	Male: -0.00 Female: -6.00	**Male** 6-11 y.o.: 1.00 12-17 y.o.: 0.00 **Female** 6-11 y.o.: 0.00 12-17 y.o.: 3.00	Male: -2.00 Female: 0.00	-	**Male** 6-11 y.o.: 0.22 12-17 y.o.: 0.35 **Female** 6-11 y.o.: 0.20 12-17 y.o.: 0.17	-	-
Aevarsdottir et al. (2017)	Tanzania	At different levels of subzidation at household level, offer to purchase solar lamps fitted with mobile phone charging point. Target population was students from primary schools.	Health outcomes as share of household members coughing, values are coefficients associated to IV estimates.	-	-	last week: -0.278 last month: -0.340 last 6 months: -0.092		-	-	-	-
Furukawa (2014)	Uganda	Distribution of solar desk lamps with market price of $ 10 USD by 2017 to 5th to 7th grade students	Students' test scores range of 100 reported by the teachers.	-	-	-	-	-	0.565***	-	Average score: -0.894* Mathematics: -0.763 English: -1.054*
Kudo et al. (2019a)	Bangladesh	**Treatment A:** 3 light solar products (164 lumens) at total cost of $ 63.5 USD by 2018. **Treatment B:** 1 solar light product (110 lumens) at total cost of around $ 40 USD. Population was 4th to 8th grade students.	Study time and school hours originally measured in minutes. Test scores are z-scores of the GPA (ranging from 0-5).	-	-	-	-	-	Treatment A: 0.22** Treatment B: 0.32 ***	Treatment A: 0.03 Treatment B: 0.05	**Treatment A:** Bengali: -0.046 English: -0.056 Math: -0.041 Gen. science: 0.052 Islam studies: 0.055 Bangladesh studies: 0.066 **Treatment B:** Bengali: 0.023 English: -0.136* Math: -0.087 General science: 0.037 Islam studies: 0.020 Bangladesh gen. studies: 0.121
Stojanovski et al. (2020)	Zambia	Provision of a solar lantern to students in grades 7-9 in 12 randomly selected schools.	Outcomes are standardized scores of a National Examination	-	-	-	-	-	-	-	Grade 7: 0.08 Grade 9: -0.10
Hassan and Lucchino (2016)	Kenya	Distribution of solar lamps to 7th grade students attending off-grid schools.	Outcomes are standardized grades, reporting ITT estimates associated to the treatment variable.	-	-	-	-	-	-	-	Mathematics: 0.88**