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Adoption and Impacts of Renewable Energy

Evidence from a Randomized Controlled Trial in Rural Kenya

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Summary

Human-driven climate disruption and widespread energy poverty are among the major challenges of our time (Alstone, 2015; SEAll, 2017). An estimated 1.1 billion people remain without access to modern energy, most of whom rely on biomass and fossil fuels for lighting, cooking, and heating — energy sources that lead to indoor air pollution and global warming (SEAll, 2017; WHO, 2016). Policy makers, entrepreneurs, and researchers across the globe place high hopes on renewable energy, particularly off-grid solar, to provide cheap and clean energy to those without access to the electric grid. The hope is that off-grid solar can reduce harmful and warming emissions from kerosene combustion and, at the same time, improve access to modern energy for unelectrified households. Despite this excitement, there is still little empirical evidence that there is demand for this technology solution, that it brings about the hoped for environmental and health effects, and that it confers private returns. It seems particularly relevant to evaluate the impact of this technology in a real-world setting since, previously, both private and environmental gains from novel technologies, such as cookstoves, have been overestimated (Hanna, Duflo & Greenstone, 2016).

This thesis investigates take-up, use, and impacts of off-grid solar lighting in rural Kenya. To this end we conducted a randomized control trial with over 1,400 households. We begin by providing an analysis of the demand for solar lights, their environmental and health effects as well as the private returns to households (Chapter 2, joint work with I. Günther). We find that access to a solar light leads to a reduction in kerosene consumption of over 1.4 liters per month, curbing emissions at a cost of less than US \$6 per ton of CO_2 equivalent. This cost is low compared with the frequently cited Social Cost of Carbon (SCC) of US \$50 per ton of CO_2equivalent (Revesz et al., 2017; IWG, 2015). Children's symptoms related to dry eye disease and respiratory illnesses reduce by about a fourth standard deviation and a third standard deviation, respectively. In addition, households save around 2-3% of their monthly cash expenditure. However, we do not find any effect on children's test scores. Finally, we find that reducing transaction costs increases demand 19% to 44% at a market price of US \$9, however, large price subsidies (over 55%) are needed to increase adoption rates to 70%. Price also does not seem to affect use. We conclude this chapter by suggesting that environmental and health effects combined with the high price sensitivity of demand and the fact that subsidies do not decrease use might justify subsidies in some settings.

The impact of solar lights on rural households and their environment depends heavily on whether households actually use them over time, which, as can be seen from the example of clean cookstoves, is not always the case (Hanna, Duflo & Greenstone, 2016). Measuring technology usage can be challenging, especially if respondents believe that it is socially desirable to use a device (social desirability bias). In this case, they might overreport use, which would lead to biased results. This bias has been found in several studies of technology adoption in developing countries (Wilson et al., 2016; Thomas et al., 2013). To address social desirability bias and other measurement issues, we used sensors to measure the use of solar lights. The sensors were developed for this study by an engineering team.

Chapter 3 (joint work with I. Günther and Y. Borofsky) focuses on information provided by sensor data. Specifically, we deployed sensors to gather an objective measure of solar light use. We then compared this data with survey data in order to analyze the extent to which survey data is limited by systematic and/or random error and discuss what type of questions provided more accurate answers. We learn from sensor data that households used solar lights almost every day, for four hours per day on average, mostly in the evening and the morning hours. Furthermore, we find that, on average, self-reported estimates of solar light use are very similar to sensor measurements, however, the correlation of estimates at the individual household level are weak, suggesting that random errors are large. Our findings indicate that households that used the solar lights infrequently were more likely to overreport, whereas those who used them a lot were more likely to underreport use. We also find that asking about general usage provided more accurate information than asking about disaggregated use for each hour of the day. Finally, and as the Hawthorne effect would predict, frequent visits from surveyors to a random subsample increased solar light use initially, but it had no long-term effects. Due to the novelty of both affordable solar lighting and the sensors used, this study is the first to both use sensors to study solar light use and compare sensor data with survey data at a large scale.

One of the key findings of Chapter 2 is that emissions reductions might justify subsidizing solar lights in some contexts, however, temporary subsidies can have complex and contradictory effects on take-up and use. Chapter 4 discusses the direct and indirect implications of subsidies on take-up and use in more detail. We begin by analyzing how subsidies affect use. They could lead to lower use, since paying a lower price might lead adopters to value the product less (sunk cost effect), or they might lead to poor targeting since households that do not actually need the subsidy might use it to purchase the product (selection effect). Social interaction effects could also affect adoption, as people might learn from early adopters or imitate them. We find that subsidies sharply increase demand for solar lights without compromising use, thus we do not find evidence for sunk cost or selection effects. Further, our results suggest that social interaction effects might increase the price sensitivity of demand, whereby demand decreases among households that received an offer to purchase at a high price, but tends to increase among households that received the low price. These findings have two implications. First, they suggest that social learning about the limited private returns are more likely than imitation, since in the latter case we would have expected to see increased adoption across the board. Second, they imply that social interaction effects are complements for subsidies, but that they do not increase adoption on their own.

To summarize, we find that in our setting solar lights are used a lot and substantially reduce kerosene use. They reduce warming emissions at a low cost and provide cheaper and better quality light to rural households. Moreover, we observe that further price reductions are needed to increase adoption rates above 50% and that subsidies do not affect use. Taken together, these findings suggest that subsidizing off-grid solar can be justified in some settings.

Zusammenfassung

Klimawandel und unzureichender Zugang zu Energie gehören zu den grossen Herausforderungen unserer Zeit (Alstone, 2015; SEAll, 2017). Geschätzte 1.1 Milliarden Menschen haben noch keinen Zugang zu moderner Energie, sondern nutzen Biomasse und fossile Brennstoffe für Dinge wie Beleuchtung, Kochen und Heizen. Diese Energiequellen führen zu Luftverschmutzung und tragen zur Klimaerwärmung bei (SEAll, 2017; WHO, 2016). Politische Entscheidungsträgerinnen und - träger, Unternehmen sowie Forschende aus der ganzen Welt setzten grosse Hoffnung in erneuerbare Energien und darin, dass netzferne Solarenergie Menschen ohne Zugang zu Strom mit kostengünstiger und sauberer Energie versorgen kann. Die Hoffnung ist, dass netzferne Solarenergie schädliche und erderwärmende Kerosinemissionen reduziert und nicht-elektrifizierten Haushalten Zugang zu moderner Energie ermöglicht. Derzeit gibt es allerdings wenig empirische Evidenz über die Nachfrage nach dezentralisierter Solarenergie und darüber, ob die erhofften Umwelt- und Gesundheitseffekte auch tatsächlich erreicht werden können. Ferner ist wenig über deren privaten Renditen auf der Haushaltsebene bekannt. Um diese Fragen zu beantworten, ist es erforderlich die Wirkung der Technologie an ihrem Anwendungsort zu testen, denn frühere Studien haben gezeigt, dass sowohl private Erträge als auch Umweltauswirkungen (z.B. bei verbesserten Kochöfen) überschätzt wurden (Hanna, Duflo & Greenstone, 2016).
In diesem Zusammenhang, untersucht diese Dissertation die Nachfrage, Nutzung und Auswirkungen von netzfernen Solarlichtern auf Haushalte im ländlichen Kenia. Zu diesem Zweck haben wir eine randomisierte Studie mit über 1,400 Househalten durchgeführt. Wir beginnen mit einer Analyse der Nachfrage für Solarlichter, deren Umwelt- und Gesundheitseffekte sowie deren privaten Renditen (Kapitel 2, verfasst mit I. Günther). Erstens finden wir, dass der Zugang zu Solarlichtern zu einer Reduktion von Kerosinkonsum von 1.4 Litern pro Haushalt und Monat führt, was Emissionen zu einem Preis von weniger als US \$6 pro Tonne CO_2-Äquivalente reduziert. Dieser Preis ist verglichen mit den oft zitierten sozialen Kosten von US \$50 per Tonne CO_2 tief (Revesz et al., 2017; IWG, 2015). Zweitens nehmen Symptome von Augentrockenheit und Lungenerkrankungen bei Kindern jeweils um ein Viertel beziehungsweise ein Drittel Standardabweichung ab. Drittens, sparen Haushalte 2-3% ihrer Monatlichen Barauslagen. Ausserdem zeigt unsere Analyse, dass niedrigere Transaktionskosten die Nachfrage zum Marktpreis von US \$9 von 19% auf 44% erhöhen

konnte, dass aber Subventionen, von über 55% nötig waren, um die Nachfrage auf 70% zu erhöhen. Wir finden keine Effekte der Solarlichter auf die Schulnoten von Kindern. Wir schliessen das zweite Kapitel mit der Empfehlung ab, dass Umwelteffekte - kombiniert mit der hohen Preiselastizität der Nachfrage und der Tatsache, dass Preisreduktionen die Nutzung nicht beeinträchtigen - Subventionen rechtfertigen.

Die Auswirkungen von Solarlichtern auf ländliche Haushalte und deren Umwelt hängt zu einem grossen Teil davon ab, ob die Lichter auch wirklich genutzt werden. Dies ist, wie das Beispiel von verbesserten Kochöfen zeigt, nicht immer der Fall (Hanna, Duflo & Greenstone, 2016). Die Nutzung von Technologien zu messen kann zur Herausforderung werden, insbesondere, wenn die befragten Personen denken, dass eine starke Nutzung sozial wünschenswert ist. Denn in diesem Fall können Befragte hinsichtlich ihrer Angaben zur Nutzung übertreiben, was zu verzerrten Resultaten führt (social desiarability bias). Solche Verzerrungen wurden in verschiedenen Studien über die Verbreitung von neuen Technologien in Entwicklungsländern beobachtet (Wilson et al., 2016; Thomas et al., 2013). Zur Lösung dieser und anderer Messprobleme, nutzen wir Sensoren um die Nutzung der Solarlichter zu messen. Die Sensoren wurden speziell für diese Studie von einem Team von Ingenieuren entwickelt.

Das dritte Kapitel 3, dass zusammen mit I. Günther und Y. Borofsky verfasst wurde, befasst sich mit der Information, die wir mit Hilfe der Sensoren gesammelt haben. Im speziellen geht es darum, die Nutzung von Solarlichtern objektiv zu messen und mit den Resultaten der Haushalts-/Personenbefragungen zu vergleichen. Damit können wir analysieren inwiefern die Befragungsdaten systematischen oder auch zufälligen Messfehlern unterliegen und welche Art von Fragen zu genauren Antworten führen. Die Sensordaten zeigen, dass Haushalte die Solarlichter im Durchschnitt vier Stunden täglich nutzen, vor allem in den Morgen- und Abendstunden. Zudem beobachten wir, dass die Schätzung der Nutzung durch die befragten Personen im Durchschnitt zwar sehr ähnlich zu der durch die Sensormessungen erfolgten Schätzung der Nutzung ist. Die Korrelation der Sensoren- und Befragungsmessung auf der individuellen Haushaltsebene ist aber sehr klein, was davon zeugt, dass grosse zufällige Messfehler auftreten. Unsere Resultate zeigen, dass Haushalte, welche die Solarlichter nur selten nutzen, eher übertriebene Angaben zur Nutzung machen, während Haushalte, welche die Lichter wenig nutzen eher untertreiben. Wie es der Hawthorne-Effekt vorhersagt, steigt die Nutzung der Solarlichter umso mehr je öfter die Interviewer die Haushalte besuchen. Dieser Effekt flacht über Zeit aber ab. Da kostengünstige Solarlichter und Sensoren relativ neu sind, legt diese Dissertation die erste Studie vor, die Sensoren in einer grossen Anzahl von Haushalten anwendet um die Nutzung von Solarlichtern zu untersuchen und diese mit Befragungsdaten zu vergleichen.

Ein weiteres zentrales Ergebnis des zweiten Kapitels ist, dass Emissionsreduktionen in gewissen Kontexten Subventionen rechtfertigen können. Subventionen können allerdings komplexe, und zum Teil widersprüchliche Effekte auf Kauf und Nutzung von Solarlichtern haben. Deswegen diskutieren wir im vierten Kapitel die direkten und indirekten Effekte von Subventionen. Zunächst zeigen wir, wie Subventionen die Nutzung beeinflussen. Preisreduktionen können die Nutzung verringern, wenn tiefere Preise dazu führen, dass Käuferinnen und Käufer das Produkt weniger wertschätzen (Sunk-Cost Effekte), oder, dass Haushalte das Produkt kaufen, obwohl sie es nicht wirklich benötigen (Selektionseffekte). Eine der indirekten Auswirkungen von Subventionen sind soziale Interaktionseffekte. Soziale Interaktion kann die Einführung eines neuen Produktes beeinflussen, wenn Leute voneinander lernen oder einander imitieren. Wir beobachten, dass Subventionen die Nachfrage stark vergrössern ohne die Nutzung zu verringern, finden also keine Evidenz für Sunk-Cost- oder Selektionseffekte. Unsere Resultate deuten auch an, dass soziale Interaktion die Preissensitivität der Nachfrage steigert, wobei die Nachfrage derjenigen Haushalte steigt, denen ein Solarlicht zu einem niedrigen Preis angeboten wurde und wenn sie eine hohes Preisangenot bekamen. Dieses Ergebnis suggeriert erstens, dass soziales Lernen wahrscheinlicher ist als Imitation, da wir im letzteren Fall erwarten würden, dass die Nachfrage bei allen Preisen steigt. Zweitens scheint es, dass soziale Interaktionseffekte Subventionen komplementieren und die Nachfrage nicht alleine erhöhen können.

Zusammenfassend finden wir, dass in unserem Kontext Solarlichter viel genutzt werden und die Nutzung von Kerosin substantiell senken. Sie reduzieren wärmende Emissionen zu geringen Kosten und bringen ruralen Haushalten günstigeres und besseres Licht. Zudem zeigen unsere Resultate, dass weiter Preisreduktionen nötig sind, um die Übernahmerate auf über 50% zu steigern und, dass Subventionen die Nutzung nicht beeinträchtigen. Zusammengenommen legen diese Ergebnisse nahe, dass Subventionen für netzferne Solarlichter in gewissen Settings gerechtfertigt werden können.

Chapter 1

Introduction

1.1 Relevance and Motivation

Balancing economic growth with sustainability is one of the most pressing challenges of our time. While there has been unprecedented progress in poverty reduction during the past 20 years, many of these achievements are now at risk due to human-caused climate disruption. At the same time, around one in seven people globally remain without access to modern energy. These people typically rely on biomass and fossil fuels for their household energy needs — energy sources that cause indoor air pollution and contribute to global warming (SEAll, 2017; WHO, 2016).

Policy makers, entrepreneurs, investors, and researchers across the globe hope that renewable energy as well as more energy efficient appliances will provide solutions for both of these problems by increasing access to modern energy services while simultaneously reducing CO_2emissions. In recent years, prices for solar products have plummeted, making off-grid solar a promising means of providing cheap, clean energy to poor households (Bloomberg, 2016). This trend is particularly relevant since recent (quasi-) experimental studies suggest that, at least in the medium term, the benefits of rural electrification in poor countries might not exceed the costs (Barron & Torero, 2017; Burlig & Preonas, 2016; Lee, Miguel & Wolfram, 2016b; Lenz et al., 2017; Peters & Sivert, 2016). Recent impact evaluations using empirical data from real-world settings, however, suggest that engineering projections often substantially overestimate efficiency gains from energy-saving technologies and have recurrently found that their private returns and potential to reduce emissions are much more limited (Davis, Fuchs & Gertler, 2014; Fowlie, Greenstone & Wolfram, 2018; Allcott & Greenstone, 2012). Similarly, field experiments on the use of cleaner cookstoves in developing countries have shown that lab tests have dramatically overestimated the effects of cookstoves on health and environmental outcomes. Various reasons could explain why cost savings as well as environmental gains are frequently overestimated: Households might simply not invest the necessary resources to access the new technology, or they might not use it even if they have access to it over time. Moreover, there could be rebound effects, whereby households use energy efficient lighting, cooking, or heating solutions more (or they could increase the use of other energy services) as increased efficiency reduces the cost of using them.

For these reasons, there is a need to conduct impact evaluations in a real-world setting to understand the private and public returns to such new technologies, no matter how promising they seem when tested in the lab. While there are a number of impact studies about the private returns of green technologies and their effectiveness in terms of reducing carbon in industrialized countries, evidence from low- and middle-income economies is still extremely scarce (Davis, Fuchs & Gertler, 2014; Davis, Martinez & Taboada, 2018). This research gap is particularly problematic since the largest increase in energy demand and related emissions will come from developing countries (DOE, 2017; Wolfram, Shelef & Gertler, 2012). We therefore believe that studies analyzing the effectiveness of promising green technologies, like solar lights, to reduce CO_2 emissions and energy poverty can and should provide insights for effective energy policies in developing countries.

The technology we focus on in this thesis is the off-grid solar light. Prices for solar panels and batteries decreased sharply in recent years (Bloomberg, 2016). Solar can be used in many forms ranging from large infrastructure feeding into national grids, to mini-grids, home systems, and the small, portable solar lanterns we study, which are particularly attractive for poor households since they require a relatively small up-front investment, are easy to deploy, and need limited maintenance. Moreover, unlike mini-grids, they do not pose the management and distribution problems typically associated with public goods. Solar lights, however, only provide limited access to energy and cannot satisfy energy needs beyond simple lighting and, in some cases, mobile phone charging. All chapters in this thesis present results from a randomized field experiment conducted in western Kenya with over 1,400 households between June 2015 and March 2016.

1.2 Contribution to Research

Only in recent years, as prices have come down, has off-grid solar lighting become a viable solution for low-income settings. Due to the relative novelty of such affordable products, there are only a few studies on the demand, use, and impact of this technology. Three studies focus on children's schooling outcomes (Furukawa, 2013; Hassan & Lucchino, 2016; Kudo, Shonchoy & Takahashi, 2017) and only one study analyzes children's health outcomes, though in a setting that is very different from ours[1] (Kudo, Shonchoy & Takahashi, 2018). Two studies look at a broader range of outcomes at the household level (Grimm et al., 2016a; Aevarsdottir et al., 2017). To our knowledge, no field experiment to date has focused on the impact of solar lights on environmental outcomes. More generally, there are still very few studies that measure both the private returns as well as the CO_2 savings of products intended to reduce the use of non-renewable energy in developing countries (Davis, Fuchs & Gertler, 2014). There is also very limited evidence on the demand for solar lights and how it responds to price changes. There are only a few recent papers that investigate household willingness-to-pay for solar lights using auction games (Grimm et al. 2016b; Niccolò et al. unpublished; Yoon, Urpelainen & Kandlikar, 2016), which we found to be hard to understand for our respondents and also are very different from how our partner organization and other enterprises typically operate. To our knowledge, there are no previous studies that randomize prices at the household level to measure household willingness-to-pay for solar lights. These research gaps are addressed in Chapter 2, where we discuss the environmental and health impacts as well as private returns to solar lights and provide first results about how prices affect demand.

An important aspect of understanding the environmental and health impacts of solar lights, as well as their private returns, depends on whether households actually use the solar lights. As previous studies suggest, however, measuring technology adoption with survey data alone might not be sufficient, since respondents might provide biased or imprecise answers (Wilson et al., 2016; Thomas et al., 2013). Technological advances now make it possible to use sensors to measure the adoption of novel technology in a very precise and accurate way. Chapter 3 builds on a small, but growing number of studies that use sensors to measure technology adoption in low- and middle-income countries and compares results with survey measures. A number of previous studies using sensors have been conducted on cookstoves (Ramanathan et al., 2016; Ruiz-Mercado, Canuz & Walker, 2013; Thomas et al., 2013; Wilson et al., 2016) and one studies the

[1] In their setting in Bangladesh, cooking and eating as well as other activities was typically done in the same room, leading to a much higher smoke exposure. In our setting cooking was typically done in a separate hut or outdoors.

adoption of water filters (Thomas et al., 2013). There is only one, small-scale engineering study that uses sensors to measure solar light use for around two weeks in 37 households (Gandhi, Frey & Lesniewski, 2016). In the first part of Chapter 3, we use sensors to get an objective measure of solar light use. The sensors technology recorded the times of day the solar light was used, which has not been analyzed before. In the second part of Chapter 3, we compare sensor data with survey data. This part contributes to questions about social desirability bias in survey data and whether respondents change their behavior as a consequence of being observed, as the Hawthorne effect would predict. Finally, we also contribute to the literature about optimal survey design. We build on studies discussing whether it is better to ask aggregate questions or detailed questions (Arthi et al., 2016; Daniels, 2001; De Mel, McKenzie & Woodruff, 2009; Grosh & Glewee, 2000; Serneels, Beglee & Dillon, 2016; Seymour, Malapit & Quisumbing, 2017), about optimal recall periods (Das, Hammer, & Sánchez-Paramo, 2012; Beegle, Carletto & Himelein, 2012), and to what extent the Hawthorne effect poses a threat to the validity of study results (Clasen et al. 2012; Leonard & Masatu, 2006; Simons et al., 2017).

In Chapter 2, we find that solar lights have positive effects on the environment that are probably not fully internalized by the households, which might justify subsidies. However, temporary subsidies can have complex and at times adverse effects on technology adoption, which we analyze and discuss in Chapter 4. This chapter extends a handful of recent studies about the demand for solar lights (Grimm et al. 2016b; Niccolò et al. unpublished; Yoon, Urpelainen & Kandlikar, 2016) by estimating how intra-household allocation of the solar light is affected by the subsidy, as well as whether and how subsidies affect use. In addition, we also study secondary effects of how subsidies affects sales in future periods, which has not been done before. As discussed in a number of studies (Ashraf, Berry & Shapiro, 2010; Cohen & Dupas, 2010; Dupas, 2014; Thaler, 1980) subsidies can lead to lower use, since paying a lower price might lead adopters to value the product less (sunk cost effect), or they might lead to poor targeting if households that do not actually need it take-up the product (selection effect). Moreover, temporary price reductions might lead to an expectation of lower prices in the future (anchoring effects), which would lower demand subsequently. Lastly, social interactions might affect the likelihood of purchasing a solar light. Building on Ashraf, Jack & Kamenica (2013) we discuss wether social learning changes the shape of the demand curve.

1.3 Statement of Contribution

I started my PhD after Prof. Isabel Günther had established the partnership and developed a first research design together with Solar Aid, which is promoting solar lights in Kenya, and Google.org, which has also funded the study. Prof. I. Günther and I worked closely together with Solar Aid to finalize the research design. I was mainly in charge of the data collection. In particular, I travelled to Kenya for a first scoping study, where I conducted qualitative interviews and focus groups, pre-tested the sensor technology, and established the relationship with our local partner in 2015. Subsequently, I developed survey instruments with input from Prof. I. Günther, Prof. M. Bates, and Dr. N. Lam. Innovations for Poverty Action conducted the data collection in Kenya under my supervision. I travelled again to Kenya for around five months to conduct a pilot and the baseline data collection. In Kenya, I hired a local Research Associate who oversaw the data collection and the two of us trained the field staff. I also designed and implemented a monitoring system to ensure that the study would be implemented as planned. For the field logistics, I received additional help from C. Nekesa and her research organization. In particular, she was in charge of the sensor data collection. These efforts were also supported by Y. Borofsky. K. Harrison (from SolarAid) helped hugely to facilitate collaboration with SolarAid and their subsidiary in Kenya, SunnyMoney. I travelled back to Switzerland after baseline data collection was completed, then went back to Kenya for endline data collection. The sensors and the corresponding software were developed by Bonsai Systems, a spinoff from ETH Zurich.

For my second chapter, I conducted the econometric analysis and provided the first draft of the chapter. Revisions of the draft were jointly carried out by Prof. I. Günther and me. I also received input from my other advisors, Prof. L. Casaburi and Prof. E. Miguel, as well as Prof. M. Fowlie, C. Wolfram, and J. McCasland, among others. For the third chapter, I conducted the data cleaning and construction of the data sets together with Y. Borofsky and Prof. I. Günther, who are both co-authors of the paper. I wrote the first draft of the chapter. Revisions of the draft were jointly carried out by Prof. I. Günther and me. I received comments and input from Y. Borofsky, as well as Prof. L. Casaburi. For my fourth chapter, which is based on a single-authored paper, the idea to collect network data came from Prof. E. Miguel. I developed the research question, did the econometric analysis, and the writing. Prof. I. Günther, Prof. L. Casaburi, and Prof. L. Falcao provided feedback on the draft.

Chapter 2

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

With Isabel Günther

Abstract: Human-driven climate disruption and widespread energy poverty are among the most pressing challenges of our times. Almost 1 billion people still use kerosene for lighting, which has high operational costs and contributes to global warming and indoor air pollution. Prices for solar have fallen dramatically and policy makers, entrepreneurs, and investors are enthusiastic about the potential of solar lighting to reduce harmful emissions while improving access to better energy services. However, rigorous empirical evidence on their private returns as well as the impact of solar lighting on emissions reductions and health outcomes is scarce. Applying a randomized field experiment in rural Kenya, we find that access to a solar light leads to a reduction in kerosene consumption of 1.47 liters per month, curbing emissions at a cost of less than US \$7 per ton of CO_2 equivalent. Children's symptoms related to dry eye disease reduce by about a fourth standard deviation and respiratory illnesses by about a third standard deviation. In addition, households reduce their monthly cash expenditure by 2-3%. Decreasing transaction costs can increase demand at current market price of US \$9 from 19% to 44%, but price subsidies of over 55% are needed to increase adoption rates to 70%. Sensor data reveal that subsidies do not affect usage. Environmental and health effects combined with price sensitivity of demand and no detected sunk-cost or selection effects may justify using public resources to increase adoption of solar lighting to replace kerosene.

2.1 Introduction

In this century the global community faces two critical challenges: human-driven climate disruption and widespread energy poverty (Alstone, 2015; SEAll, 2017). Acknowledging these challenges, the UN Sustainable Development Goals has called upon the international community to "ensure access to affordable, reliable, sustainable and modern energy for all." Nevertheless an estimated 1.1 billion people remain without access to modern energy, most of whom rely on biomass and fossil fuels for lighting, cooking and heating with harmful emissions for the environment and humans (SEAll, 2017; WHO, 2016).

There is a heated debate about how to improve energy access while ensuring environmental sustainability, and many believe that there are inevitable trade-offs. There are high hopes that new technologies will allow avoiding painful tradeoffs and create "win-win" situations, by simultaneously increasing energy access (or reduce energy cost) and reducing emissions. However recent studies, mostly from high-income countries, suggest that engineering projections often overestimate efficiency gains from novel technologies (such as more efficient air-conditioners and fridges or energy efficient home improvements) and studies evaluating their cost-effectiveness in a real world setting have found that their private returns and potential to reduce emissions are much more limited (Davis, Fuchs & Gertler, 2014; Fowlie, Greenstone & Wolfram, 2018; Allcott & Greenstone, 2012). Similarly, field experiments on the use of cookstoves in developing countries have shown that lab tests have overestimated their effects on health and environmental outcomes, and in many instances the improved cookstoves are hardly used (Hanna, Duflo & Greenstone 2016).

Projections based on lab tests might overestimate cost savings and environmental gains from novel technologies for a number of reasons. First, households might not invest the necessary time and effort to access them. Second, they might not use and maintain new technologies over time. Third, there could be rebound effects, whereby households use the more energy efficient solutions more, or increase the use of different energy services, as they are cheaper to use. The result is that overall spending on energy and emissions are not reduced as much as previously thought (Fowlie, Greenstone & Wolfram, 2018; Gillingham et al., 2013; Van den Bergh, 2011). Finally, projections might be simply overly optimistic about their economic returns as they overestimate the costs of current solutions or underestimate "hidden" costs of the new product (Fowlie, Greenstone & Wolfram, 2018). Therefore, there is a need for impact evaluations that study the effect of new technologies in a real world setting. While there are a number of studies about the cost- and environmental effectiveness of carbon reducing technologies for residential energy in developed countries, evidence from developing economies is still very scarce (Davis, Fuchs & Gertler, 2014; Davis, Martinez & Taboada, 2018). This is particularly problematic as the largest increase in energy demand will come from developing countries (DOE, 2017; Wolfram, Shelef & Gertler, 2012).

In recent years, prices for solar panels and batteries have decreased dramatically and made off-grid solar a seemingly cost-effective solution to provide poor households with cheap and clean energy (Bloomberg, 2016). This is particularly relevant as electrification, which is the most obvious alternative to off-grid solutions, might be more expensive and less transformational in some rural settings than previously thought. In fact recent (quasi-) experimental evidence suggests that, at least in the medium run, rural electrification in poor countries might not be cost-effective (Barron & Torero, 2017; Burlig & Preonas, 2016; Lee, Miguel & Wolfram, 2016b; Lenz et al., 2017; Peters & Sivert, 2016).

Emissions from kerosene lamps contribute to global warming and indoor air pollution (Lam et al., 2012a; Jacobson et al., 2013), which is a leading risk factor for disease (WHO, 2016). The hope is that solar lighting would replace the widespread use of kerosene for lighting, allow low-income households to significantly decrease their energy expenditure, and reduce the associated emissions and related health risks.

Our study provides experimental evidence on the impact of solar lights on kerosene use and the associated effects on CO_2emissions, indoor air pollution, and health of household members. Due to the novelty of affordable solar lighting solutions, there are only a handful of studies on the impact of this technology. Three studies have focused on whether access to solar improves children's schooling outcomes (Furukawa, 2013; Hassan & Lucchino, 2016; Kudo, Shonchoy & Takahashi, 2017) and two studies have looked at a broader range of outcomes at the household level (Grimm et al., 2016a; Aevarsdottir et al., 2017). Only one study has focused on the effect on children's health outcomes (Kudo, Shonchoy & Takahashi, 2018).

To our knowledge, no field experiment to date has evaluated the climate-related impact of solar lights. Such an assessment is highly dependent on an accurate estimate of the use of solar lights of household. Measuring the use of new technologies with surveys only is challenging, as respondents might be tempted to overreport usage, leading to social desirability bias in estimates (Wilson et al., 2016; Thomas et al., 2013). We therefore used sensors, specifically developed for this project, for accurate high-frequency measures of solar light use.[2]

However, even if the use of solar lighting reduced the negative effects of kerosene use on global warming and indoor air pollution, households might still not invest in solar lights as they do not fully internalize these benefits or might not be aware of them. There are a number of additional reasons why households might invest less in solar lights than what is socially optimal. First, they might underinvest due to present bias and inconsistent time preferences, which has been shown for different preventative health products before (Dupas, 2011; Dupas, 2014; Kremer & Miguel, 2007). Second, they might be overly risk averse and hesitant to invest in a technology with unknown return and lifespan. Third, households might be too credit-constraint to invest in the substantial up-front payment. Finally, there could be issues related to intra-household allocation: children might benefit particularly from the solar light as they can use improved light for their homework. The household's financial decision makers might underinvest as they do not fully internalize children's preferences. Hence, we also need to understand the private economic benefits of solar lights for households and, if limited, analyze whether subsidies would increase the adoption of this new technology without compromising its usage. Subsidies might affect use as paying a lower price for a good might decrease its perceived value and makes people less likely to use it (sunk-cost effect) or people who are less interested in the product might purchase it and use it less (selection effect). We address both questions in the second part of this study.

We conducted a randomized field experiment with over 1,400 households in the rural areas of Western Kenya, where less than 5% of the population were connected to the electricity grid at the time of the study. Households either received a free solar light, an offer to buy a solar light at a high discount (US $4), a low discount (US $7), the market price (US $9), or they were randomly assigned to a control group and received no intervention. In addition to a household survey before and after the intervention, we installed sensors measuring the use of solar lights in a subset of households and collected children's test scores before and after the intervention.

We find that access to a solar light reduces kerosene use by 1.47 liters on average per month, leading to yearly emissions abatement of 828.47 kg of CO_2equivalent

[2] Results from sensor measurements are discussed in Chapter 3 in detail.

per household. If this was scaled to all households using kerosene in Kenya, this could decrease emissions by 2.17 mega tonnes of CO_2 equivalent, corresponding to 3.58% of Kenya's overall emissions in 2014 (CAIT, 2017). We estimate that the price per tonne of CO_2 equivalent averted is between US $5.87 and to US $9.69, which is lower than what is typically considered as the social cost of carbon (IWG, 2015) and also lower than clean energy investments in Europe or the US (Abrell et al., 2017). Access to solar lighting also decreases symptoms of dry eyes disease for both children and adults and symptoms for respiratory illness for children. The private returns are more modest, with households saving around 102.4 KES (US $1.02) per month corresponding to 2%-3% of total cash expenditure. We do not find any effects on children's test scores in school. Our results also suggest that demand for solar lighting is very price sensitive. At current market conditions and prices US $9 demand is modest with 19% of households owning a solar light. We find that decreasing transaction costs alone can increase demand to 44% but price reductions are needed to increase take-up further.

2.2 Background and Study Design

2.2.1 Context

Only 1.6% of the Kenyan population used solar as their main lighting source in 2005 (KIHBS, 2018). In 2008, Lighting Africa, an initiative led by the World Bank and IFC, selected Kenya together with Ghana as pilot countries to support the off-grid solar sector through a variety of measures, including product quality verification, costumer awareness campaigns, provision of market intelligence and technician trainings to provide after-sales maintenance support (Lighting Africa, 2016). In 2014, the Government of Kenya exempted solar products from the Value Added Tax of 16%, which reduced the price for end users (GoK, 2014). The share of household who use solar as their primary energy source for lighting has increased to 14.1% by 2015, but annual sales have stagnated since (GOOGLA, 2018;KIHBS, 2018).

The Government of Kenya has stated that it wants to eliminate kerosene for household energy consumption due to health and environmental concerns.[3]

[3] See for example Kenya's Climate Change Action Plan "When used in simple kerosene lamps, kerosene leads to high indoor air pollution as well as to an increased risk of burns, fires and poisonings" (GoK, NCCAP, 2012). Kenya's Energy Policy states that "Increased use of

Moreover, in response to the Paris Agreements, the Government of Kenya announced that it intends to reduce its CO_2 emissions by 30% compared to a "business as usual" scenario by 2030 (GoK, 2015) and developed a National Climate Change Response Strategy and Action Plan (GoK, NCCAP, 2012). As a result, there is an ongoing debate about the government's energy policy and how it should balance concerns over access with environmental sustainability. For example, the Government of Kenya currently discusses how much kerosene should be taxed; while some argue that environmental and health concerns justify taxes, other fear that poor households will be hit hard by increasing kerosene prices and won't be able to access sufficient lighting anymore (GoK 2012; Daily Nation, 2018).

At the same time the Government of Kenya has also heavily invested in rural electrification to increase access to energy for its population. The ambitious goal is universal access to electricity by 2020 (GoK, 2015). In 2013 the Rural Electrification Agency announced that 90% of the country's public facilities were electrified and thus a large share of the population lived within proximity of the grid. However, only 18-26% of households were electrified at the time. In 2015 the Kenyan government announced that they raised additional US $364 million for the "Last Mile Connectivity Project", mostly from the World Bank and the African Development Bank (Lee, Miguel & Wolfram, 2016b). This project provides large subsidies so that connections for those living close to the grid would only cost US $150 for the individual households (Lee, Miguel & Wolfram, 2016b; Kenya Power, 2017). According to the Kenya Power and Lighting Corporation (KPLC), this has led to almost 50% of households connected to the electricity grid in 2016. The program was still in its early stages during the time of our study in 2015 and the villages we worked in remained largely unaffected. Only 1.4 % of households in our sample were connected to the grid and only 13 households heard about an electrification project in their village. The costs for grid connection was still at 35,000 KES (US $350) during our study.

2.2.2 Intervention

While a number of different types of solar products are sold on the Kenyan market, we analyze the impact of low-cost solar lights — small portable lighting

LPG shall be encouraged with a view to eliminate the use of kerosene, charcoal and firewood in households" , GoK, NEPP (2015).

units. Our study partner was SolarAid, one of the largest local distributor of portable solar lights at the time of the study. From 2009-2015 our partner sold over 1.7 million solar lights through its subsidiary SunnyMoney, most of them in Tanzania, followed by Kenya (SolarAid, 2015). Two different types of lights were studied: the Sun King Eco and the Sun King Mobile, both manufactured by Greenlight Planet and quality assured by Lighting Global, a World Bank initiative. According to tests conducted by Lighting Global, the Sun King Eco provides light for 5.8 hours when used at its maximum brightness of 32 lumens, [4] and up to 30 hours when used at its least brightest mode of 4 lumens, according to the manufacturer (Greenlight Planet, 2016; Lighting Global, 2015). The Sun King Mobile can be used for 5.4 hours in its brightest mode (98 lumens) and 10.3 hours in its medium mode (51 lumens) (Lighting Global, 2015). The Sun King Mobile can also be used to charge a mobile phone.

For comparison, a simple kerosene tin lamp provides around 7.8 lumens and a kerosene lantern 45 lumens (Mills, 2003). A picture can be found in the Appendix (Figure A.1 and A.2). Both types of solar lights hence provide a stronger light than the tin lights, which are used as the primary lighting source by 27.7% of Kenyas rural population (KIHBS, 2018). In 2015, our partner organization was selling the Sun King Eco light for US $9 in Kenya, and the Sun King Mobile at US $24, corresponding to 12.3% and 32.8% of a household's average monthly cash expenditure.

2.2.3 Experimental Design

We conducted a randomized control trial (RCT) between June 2015 and March 2016 in Nambale and Teso South, two sub-counties located in the Busia County in Western Kenya. In a first step, we randomly selected 10 schools in each of the sub-counties out of a total of 97 eligible schools that met a pre-specified set of criteria.[5] Within each of these 20 schools, we identified all households that

[4] Lumen measures the brightness of a lighting source (i.e. the amount of visible light is emitted). Watt on the other hand are used to indicate the amount of energy needed to power the product. A 3-5-watt compact fluorescent lamp corresponds to around 110 lumens.

[5] The local administration provided a list of all 127 public schools (50 in Nambale and 77 in Teso South). A number of schools were eliminated, such as schools with less than 100 pupils, schools with only girls or only boys, boarding schools, schools located in urban centers or that were too far from the research office to be reached within a field work day, and schools whose head teacher was not present at the term head teacher meeting, where our partner organization typically recruited head teachers for their solar program. From the remaining 97 schools, 20 were selected at random (10 in each sub-county).

had at least one pupil in class five, six, or seven. Class eight was not included since these pupils would have left school by the time the endline survey was conducted. Students in lower classes (1-4) were not invited to participate in the study since it would have been harder for them to answer questions about homework, time use, light use, etc. In a second step, out of the 3,360 eligible households (with at least one child in class five, six, or seven in the 20 schools in our sample) a total of 1,410 households were randomly selected to be part of the study (Figure 2.1).[6]
Randomization into different treatments was then conducted at the household level and stratified at the school level, or in other words we randomly selected around 70 households per school, leading to 1,410[7]selected households across all 20 schools and randomly assigned them into one of several groups.

1. Control group: 20 households per school, 400 households total.
2. Free solar lights group: 20 households per school, 400 households total, received a free solar light, of which 200 received a solar light that also had a port to charge a mobile phone.
3. Voucher group: About 30 households per school, 610 households in total, received a voucher to purchase a solar light at one of the following prices:

    - Subsidized price of 400 KES /US $4 (N=209)
    - Subsidized price of 700 KES/US $7 (N=201)
    - Market price of 900 KES/US $9 (N=200)

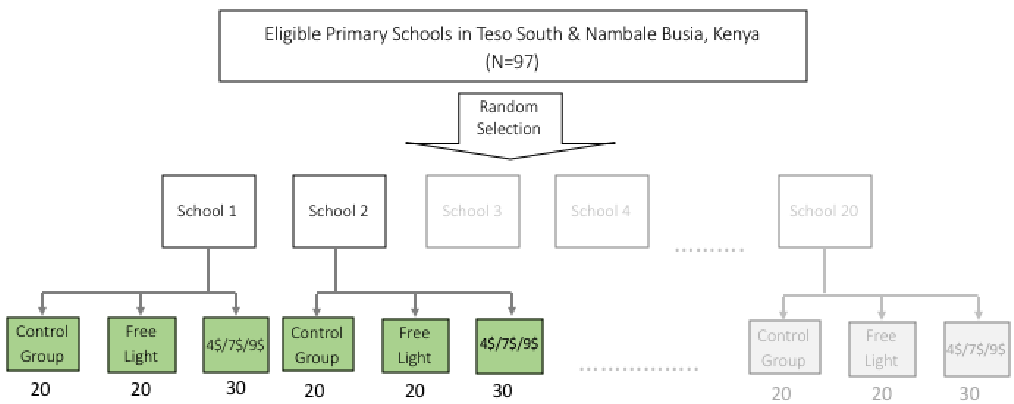
In each household, we surveyed the selected child and the child's main caretaker. We designed a lottery based on text messages, to make it clear to respondents, that whether they won a prize was decided by random chance. The lottery worked in the following way: at the end of the baseline interview surveyors gave

[6]Visits to schools were announced in advance and children were encouraged to come to school; however, if a selected pupil was absent that day s/he was replaced with another pupil who was drawn at random.

[7]Two of the schools did not have enough households that met the selection criteria. In these two schools, we reduced the number of vouchers distributed to 0 (Sango) and to 10 (Aburi) and increased the number of sampled students in larger schools instead. To keep field operations as simple as possible we increased participation to 75 (Opeduru, Olepito, Obekai, Kaliwa, Kamarinyang, Ong'aroi, Asinge, Ng'eechom) or 80 (Sianda, Khayo) in other schools.

respondents a "lucky number" and invited them to participate in the lottery. The respondent then sent a text message with the "lucky number" to participate in a lottery and immediately received a text message back, announcing if they either won a free solar light, had the opportunity to purchase one at a given price during the following weeks, or did not win anything (control group). This text message could then be redeemed to either receive a free solar light on the spot or a personalized voucher. As these types of text-message games are very common in Kenya, it was easy to understand for respondents and made it clear that the allocation of prizes was random.[8]

Figure 2.1: Research Design



Notes: We randomly selected 20 schools (10 in each sub-county) out of 97 eligible schools. Randomization into treatments was conducted at the household level and stratified at the school level.

In the end of the baseline interview, field staff showed the solar light to every guardian who received an offer to purchase one and read a script containing basic information (Appendix, Section E) about the solar light. All vouchers contained the respondent's name and were not transferable. We conducted audits to ensure that the respondents did not sell or trade their vouchers. Respondents could

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

Table 2.1: Balance Table for Main Outcomes

Stats	(1) Control Mean (SD)	(2) Free Mean (SD)	(3) Diff. [P-Val]
Kerosene Used (l)	3.106	3.070	0.036
	(3.744)	(4.027)	[0.897]
Kerosene Spent (KES)	211.536	200.669	10.867
	(145.986)	(158.271)	[0.318]
Adults Dry Eyes 0-6	3.005	2.920	0.070
	(1.886)	(1.878)	[0.597]
Pupils Dry Eyes 0-6	4.178	4.000	0.170
	(3.429)	(3.603)	[0.498]
Adults Respi. 0-5	1.538	1.585	-0.055
	(1.551)	(1.590)	[0.620]
Pupils Respi. 0-5	0.703	0.673	0.032
	(0.457)	(0.470)	[0.331]
Nr of Kerosene Lights Used	2.545	2.583	-0.038
	(1.112)	(1.125)	[0.635]
Nr of Calls	16.469	14.639	1.829
	(18.619)	(18.858)	[0.271]
Times Phone Charged	1.485	1.447	0.038
	(1.249)	(1.207)	[0.665]
Homework Completion	0.674	0.652	0.022
	(0.470)	(0.477)	[0.559]
Homework Hours	2.198	2.208	-0.003
	(1.599)	(1.626)	[0.976]
Sleep Hours	7.276	7.352	-0.106
	(3.383)	(3.395)	[0.661]
Average Test Scores	-0.005	0.045	-0.053
	(0.999)	(1.020)	[0.486]
Observations:	398	398	796

Notes: Sample restricted to control group and free solar light group, since we only have few baseline measures for groups that received a voucher to buy a solar lantern. Number of observations is indicated for adult surveys. We had 793 pupil surveys (396 in the Control Group and 397 in the Free Group) but only 718 (355 in the Control Group and 363 in the Free Group) observations for test scores.

Table 2.2: Summary Statistics and Balance Table

Stats	(1) All Mean (SD)	(2) Control Mean (SD)	(3) 400 Diff. [P-Val]	(4) 700 Diff. [P-Val]	(5) 900 Diff. [P-Val]	(6) Free Diff. [P-Val]	(7) All Diff. [P-Val]
Iron Roof	0.646	0.666	0.060	0.045	0.036	-0.003	-0.028
	(0.478)	(0.472)	[0.143]	[0.278]	[0.381]	[0.940]	[0.331]
HH Head Female	0.303	0.309	0.016	0.022	0.040	-0.018	-0.008
	(0.460)	(0.463)	[0.689]	[0.587]	[0.315]	[0.595]	[0.757]
Household Size	6.688	6.784	0.178	0.143	-0.023	0.183	-0.134
	(2.141)	(2.177)	[0.345]	[0.456]	[0.902]	[0.218]	[0.293]
Main Income is Agriculture	0.683	0.688	-0.013	-0.004	-0.017	0.038	-0.008
	(0.466)	(0.464)	[0.733]	[0.924]	[0.670]	[0.259]	[0.770]
Business Ownership	0.294	0.332	0.014	0.111 ***	0.103 ***	0.018	-0.052 *
	(0.456)	(0.471)	[0.721]	[0.005]	[0.009]	[0.596]	[0.054]
Yrs of Schooling HH Head	6.386	6.599	0.549 *	0.334	0.069	0.251	-0.295
	(3.804)	(3.895)	[0.096]	[0.336]	[0.838]	[0.378]	[0.206]
Number of Mobile Phones	1.397	1.425	0.040	0.033	0.024	0.048	-0.038
	(0.794)	(0.802)	[0.550]	[0.634]	[0.733]	[0.411]	[0.414]
Solar Lantern Ownership	0.065	0.053	-0.029	-0.009	-0.018	-0.015	0.017
	(0.247)	(0.224)	[0.163]	[0.662]	[0.373]	[0.372]	[0.235]
Access to Electricity	0.014	0.013	-0.016	-0.003	0.002	0.003	0.002
	(0.119)	(0.112)	[0.154]	[0.780]	[0.798]	[0.738]	[0.726]
Total Expenditure	7,319.549	7,405.847	-	-	-	171.938	-
	(5,461.814)	(5,407.505)				[0.657]	
Land Owned	2.035	1.977	-	-	-	-0.114	-
	(1.455)	(1.793)				[0.388]	
Chickens Owned	6.043	6.156	-	-	-	0.226	-
	(5.138)	(6.396)				[0.598]	
Earth Floor	0.883	0.864	-	-	-	-0.038 *	-
	(0.608)	(0.343)				[0.098]	
Observations:	1396	398	208	195	197	398	1396

Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns 3-6 show differences with mean of the control group (Column 2). Some are missing since as discussed in Section 2.2.4 we do not have all baseline variables for the voucher group. Column 7 shows difference of all groups with control group.

redeem their vouchers through the head teacher of the participating schools within 4-6 weeks.[9] This means that those who received an offer to purchase a solar light (including at market price) could buy the solar light in an easily accessible place (their child's school) without high transportation costs, whereas household from the control group could only purchase the solar light through local retailers. We learned through our surveys that solar lights where not always easily available, as only 7.52% of the sampled households said that they could be bought in their village and 43.41% in the closest market center.

2.2.4 Estimation Strategy

Our main specification for the analysis of impact is an instrumental variable (IV) approach to estimate the Local Average Treatment Effect (LATE). The LATE is the effect of having a functioning solar light (either having received a free one or having bought one through our program) on the various outcomes of interest.[10] We use the randomly allocated treatment group (either voucher to purchase a solar light for 400 KES, 700 KES or 900 KES or receiving a free Sun King Mobile or Sun King Eco light) as an instrument. The treatment status affects the probability of having a functioning solar light strongly and should not affect the outcomes of interest through any other channel than through having a functioning solar light. Using this identification, we combine the treatment effects of the different subsidies into one. In Section 2.3.4 we show that there is no significant difference in solar light usage for households that receive a free solar light in comparison to solar lights who have to pay US \$4, \$7 or \$9.
Formally we estimate the following set of regressions:

$$light_{ij} = \alpha_0 + \sum_{k=1}^{5} \alpha_k (offer_{ij}) + \beta X'_{ij} + \lambda_i + \epsilon_{ij} \quad (1)$$

$$y_{ij} = \alpha_0 + \alpha_1 (\hat{light}_{ij}) + \beta X'_{ij} + \lambda_i + \epsilon_{ij} \quad (2)$$

$light_{ij}$ designates whether household i in school j had a functioning solar light at endline, $offer_{ij}$ designates the type of offer the household received, which was either a free Sun King Eco light, a free Sun King Mobile light or a voucher to purchase a Sun King Eco light (for 400 KES, 700 KES or 900 KES). X_j

[9] This was how our partner SunnyMoney typically operated.

[10] For simplicity, we use the following terms "effect of having access to a solar light " or the "effect of solar lights" etc. to describe the LATE.

refers to a set of control variables namely electricity connection at baseline, business ownership and wether anyone in the household is employed as well as household size. The regressions shown in the main paper are without controls, with the exception of gender of the respondent, if the relevant outcome is at the individual level and class fixed effects for children's outcomes. Regressions with the controls mentioned above are shown in the Appendix. The results do not change significantly. λ_i refers to school fixed effects (we stratified at the school level). ϵ_{ij} is an error term. y_{ij} designates the outcome of interest of household i in school j and α_1 captures the LATE.

Due to budget constraints, we do not have all baseline measures for all outcome variables of interest for the entire sample (only for the free solar light and the control group). Therefore we cannot control for baseline measures of our dependent variables. Table 2.1 shows that the sample is balanced between the free and the control group across all outcomes of interest, Table 2.2 shows that the sample was mostly balanced across a number of other household characteristics across all treatment groups.

For full transparency and as outlined in our pre-analysis plan we provide the Intention-To-Treat (ITT) measures of our main results in Table 2.12.

2.2.5 Data

Prior to commencing the full study, we conducted a number of in-depth interviews with solar light users and non-users, with teachers as well as field staff and executives from our study partner SunnyMoney. We also held five focus group discussions with users and non-users of solar lights. The information from the in-depth interviews and focus groups was used to design the survey instruments. In addition, we tested the random distribution of free lights, as well as the survey questions and the acceptability of the sensor technology before running the full baseline survey.

We surveyed the randomly selected pupils (see Section 2.2.3) as well as their primary guardian, which in most cases was the mother (50.2%) or the father (28.7%). Data were collected at baseline (July/August 2015) before the intervention and around seven months after baseline (February/March 2016). We created survey instruments based on previous studies conducted by leading researchers in the field of renewable energies in low-income countries, including Cattaneo et al. (2009), Furukawa (2013), Grimm et al. (2016a) and Lee, Miguel & Wolfram (2016b), as well as standardized scales to measure health and well-being (World Value Survey, European Community Respiratory Health Survey II and the Standard Dry Eyes Disease Questionnaire and CES-D).

The main outcomes of interests are different measures of kerosene used, energy spending, indices to measure health outcomes, light and phone use as well as homework completion and test scores, time children spent doing homework and other activities.

In addition to survey data, which, in most cases, are self-reported by respondents, we used sensors to measure light use. A random sub-sample of the solar lamps that were distributed free or purchased at 700 KES (US $7) or 900 KES (US $9)[11] were equipped with Bluetooth-enabled sensors developed by Bonsai Systems.[12] Respondents were informed before downloading the data about the sensor and asked for permission to access the data. No data were downloaded if the participant had any objections. Sensors tracked when the solar lights were used and for how long, by measuring the change in voltage across the device's light emitting diode (LED). Using smartphones enabled with Bluetooth and an iPhone application called "Lamplogger" (which was specially developed for this project), field officers visited households and wirelessly uploaded data from the sensor to the phone. These data are primarily used in Chapter 3.

To receive an additional and more objective measure of educational outcome, we also collected school-level test score information before the study started (March 2015), as well as after the study ended (March 2016). Test scores were collected for all tested subjects: Math, Swahili, Science, English, and Social Studies.

2.3 Energy and Light Use at Baseline

At baseline, the average household in our sample had 6.7 members, with 4.3 children under the age of 18. The average household head attended school for 6.4 years (Table 2.2, Column 1). Most houses had earth floors (88.3%) and iron sheet roofs (64.6%) on their main building. The average household spent US $73.2 in cash per month, or US $10.93 per person and month. Expenditures captured here do not include items that households consume from their own farms, which constitutes a large fraction of overall consumption for many rural households. A typical household owned 2.0 acres of land, 1.3 cows, and 6.0 chickens (Table 2.2, Column 1). Slightly more than half (53.8%) of households

[11] However due to logistical difficulties not all lights sold at a price price were equipped with a sensor.

[12] http://www.bonsai-systems.com

owned a bicycle, but only 7.8% a motorbike. Almost all households (98.8%) conducted agricultural activities and for 68.3% of households this remains the main income source. About a third (29.4%) owned a business, however mostly without any employees, usually selling fish or other food items. Only 20.1% of the households had one member or more who were employed in the previous year (formally or informally). Hence, the households sampled in our study depend largely on agriculture, live in basic housing, and are poor - even when compared to the average in rural Kenya (KIHBS, 2018).[13]

In the beginning of our study only 4.2% of the sampled households had access to some form of electricity. To break this number down: 1.4 % of households were connected to the grid, 1.1% had access to a solar home system, 1.5 % had access to a car battery, which provides energy for the household, and 0.1% had access to a generator. Most of these households were using the respective electricity source for their radio (80.0%), for lighting (72.0%) or to charge their mobile phones (65.4%). Just less than a third (32.0%) used electricity to watch TV, and 20% for ironing. No one had a fridge and no one used the energy source for activities that are potentially income generating such as sewing, water pumping or irrigation.

The vast majority of the sampled households (98.4%) used an open fire for cooking. Charcoal, kerosene, LPG, and other stoves are not common. As opposed to other settings, where eating and cooking happens in the same room (see for example Kudo, Shonchoy & Takahashi, 2018), people in the region of our study cook in a separate building or outdoors (93.3%) and only 6.7% cook in the same house as they eat. The relative importance of lighting as a source of indoor air pollution is larger in settings where people cook in a different place (Lam et al., 2017).

Most households (88.4%) rely on small locally produced kerosene lights (tin lanterns) for lighting (Appendix, Figure A.1). Others use larger kerosene lanterns (5.3%) (Appendix, Figure A.2), solar lights (3.8%), and only 1.1% use electricity-powered lighting as their primary lighting source. On average, a household owns 2.1 tin lamps. Tin lanterns can be bought for US $0.25-$0.50, depending on the size and quality of the lamp. Kerosene lanterns cost between US $3-$6. They also use more kerosene per unit of time and are therefore more expensive to operate (Mills, 2003). Every household that uses grid electricity also uses at least

[13] According to the 2015/6 Kenya Integrated Household Budget Survey 83.2% of the rural population had iron roofs and only 43.2% earth floors, meaning that they stay in better quality housing than the average in our sample.

one other source of lighting — probably a reaction to the frequent blackouts in the study region. During baseline an average household spent around US $3.61 (360.9 KES) per month on energy, corresponding to 4.9% of the households' total cash expenditure.[14] Energy expenditures are mostly on lighting. For kerosene alone, households spent US $2.06 (206.1 KES) per month, which corresponds to 57.1% of the total energy expenditure and 2.8% of total cash expenditure. These numbers are similar to national representative surveys of Kenya (KIHBS, 2005/2006; Lighting Global, 2012) as well as what other studies find (Kudo, Shonchoy & Takahashi, 2017; Grimm et al., 2016a). Monthly household energy expenditures unrelated to light use include expenditure on mobile phone charging (US $0.42), charcoal (US $0.24), batteries not used for lighting (US $0.30), firewood (US $0.21), and electricity bills (US $0.18).

2.4 Reducing Emissions

The use of kerosene for lighting contributes to indoor air pollution and global warming. Emissions from one tin lamp can increase indoor small particles (PM 2.5)[15] concentrations around 10 times above WHO guideline levels (Apple et al., 2010). Some studies even suggest that particles generated by kerosene combustion might be more toxic than wood-smoke (Lam et al. 2012b; Pokhrel et al., 2009; Bates et al., 2013; Epstein et al., 2013). In addition, 95% of the PM2.5 that kerosene lights emit are black carbon (BC), which is estimated to be around 700 times more warming than CO_2 (Lam et al., 2012b). Kerosene lights also directly emit a small amount of CO_2. While the literature on the subject is still limited, Lam et al. (2012a) estimate that the combined emissions of kerosene used in households worldwide have the same warming effect as 4.5% of total United States' CO_2 emissions and is therefore non-negligible.

Access to a solar light leads to a significant reduction in kerosene use of households and associated emissions (Table 2.3). A typical household keeps using kerosene as it would replace one of their two kerosene lights with a solar light (Table 2.3, Column 1). Some households also stopped using kerosene once they got access to a solar light. In fact, having access to a solar light reduced chances of using a kerosene-based products the previous evening by 29.5 percentage-

[14] To provide a reference for comparison, European households spend on average around 4% of their total expenditure on electricity, gas, and other fuels used by the household in 2011 (Eurostat, 2011 retrieved from http://ec.europa.eu/eurostat/statisticsexplained/index.php/Archive:Household_consumption_expenditure_-_national_accounts)

[15] PM 2.5 are fine particulate matter fine of inhalable particles, with diameters that are 2.5 micrometers and smaller.

points (Table 2.3, Column 2). On average, households reduce their kerosene use by 1.47 liters[16] per month (Table 2.3, Column 5).

Table 2.3: Impact on Kerosene Use and Emissions

VARIABLES	(1) Nr of Kerosene Lights	(2) Used Ker Yest.	(3) Tins Kerosene Use (l)	(4) Lantern Kerosene Use (l)	(5) All Kerosene Use (l)	(6) Monthly PM 2.5 (g)	(7) Monthly BC (g)	(8) Monthly CO2eq (kg)
Solar Works	-1.028***	-0.295***	-1.207***	-1.814***	-1.471***	-97.582***	-93.887***	-69.039***
	(0.109)	(0.038)	(0.314)	(0.411)	(0.259)	(18.495)	(17.891)	(13.080)
Lower Bound	-0.814	-0.220	-0.592	-1.008	-0.963	-61.332	-47.729	-43.402
Upper Bound	-1.242	-0.369	-1.823	-2.620	-1.978	-133.831	-133.8	-94.676
Observations	1,313	1,313	957	342	1,299	1,291	1,291	1,291
R-squared	0.130	0.186	0.054	0.248	0.075	0.070	0.070	0.070
School FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO	NO	NO	NO
Control Mean	2.234	0.837	2.502	2.265	2.445	164.9	158.8	116.7

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Column 3 shows the reduction for households that only use tin lights, Column 4 for those using kerosene lanterns only and Column 4 for everyone else. Columns 6-8 show information for both types of households. In Column 6-8 we used the following factors: if a household uses tin lanterns only 90g of BC/kg of Kerosene, 93g of PM2.5/kg of Kerosene and 2770g of CO2eq/kg of Kerosene. If the household only uses kerosene lanterns 9g of BC/kg of Kerosene, 13g of PM2.57kg of Kerosene and 3080 g of CO2eq7kg of Kerosene. All factors are based on Lam et al. (2012). The 13.79% of households that use both types of lanterns we use a simple average of both values. For 8 households we do not know the types of lanterns they use, hence they are missing on Columns 2-4.

We used information from a study that was conducted in Uganda, where PM2.5 as well as BC emissions of tin lamps and kerosene lamps were measured (Lam et al., 2012), to estimate how reductions in kerosene use translate into emissions reductions. The relationship between fuel burned and emissions is linear. To estimate emissions reductions, the decrease in kerosene use per households can therefore be scaled by the relevant factor of PM2.5 and BC emissions per liter kerosene burned. Note that these factors are much larger when the kerosene is

[16]This is based on survey answers about the amount of kerosene purchased previous week.

burned with a tin light as opposed to a larger kerosene lantern. In our sample, 73.65% only used tin lamps during the past month[17], 13.79% used both, tin lights and kerosene lanterns and 2.13% only kerosene lanterns. The remaining 10.43% did not use any kerosene based lighting products in the past one month. For households that used both kerosene and tin lights, we used a simple average of the factors for tin and kerosene lights. When we convert BC into CO_2 equivalents, we also add the small amount of CO_2, which additionally gets emitted by kerosene combustion (calculations are conducted at the household level and conversion rates are based on Lam et al., 2012b). We find that a typical household reduces its emissions by 97.58 g of PM2.5 and 93.89 g of BC and 69.04 kg of CO_2 equivalents per month (Table 2.3, Columns 6-8).
Based on the estimates in Table 2.3, assumption of a cost of US $9 per solar light, a lifetime of two years, and 48 kg of CO_2 embedded in the light from the production (based on Alstone et al., 2014)[18] as well as a 3% yearly discount rate for CO_2 emissions (based on IWG, 2015) and a failure rate of 1.15% per month (based on our study), we estimate an abatement cost of US $5.87 per ton of CO_2 equivalent (Appendix, Table A.3). While we do not have detailed program cost estimate, we assume that US $9 per household is a conservative estimate as this is the price at which quality solar lights could be purchased on the private market at the time of the study. However the price has further reduced since (Bloomberg, 2016; IFC, 2018). This only reflects the reduction in CO_2 equivalents and does not consider any other benefits such as health effects and households savings, which we will discuss later. However, this estimate is sensitive to the share of the targeted population that uses kerosene based products for lighting in the first place, as well as the share of tin vs. kerosene lamps that are used. This is relevant because the latter's emissions are much smaller (Lam et al. 2012b). In our sample the share of tin light users was larger than in the country as a whole, as our respondents tended to be poorer. Note also that households in our study only got access to one solar light, which typically allowed them to replace one of their kerosene lights. However most households used two kerosene lanterns and replacing the second one would reduce their

[17] We asked what lighting sources were used in the past one month.

[18] The solar lights assessed by Alstone et al. 2014 are not exactly the same types as the ones used in this study. We used estimates that are most comparable with the ones we used in our study. Based on Dones et al. we then estimated that 27.78 kg of CO_2 are emitted per KwH of energy used to produce the solar lights. This is a rather conservative estimate as we assume that all parts of the lights are produced with coal energy in inefficient power plants in China. Using this back of the envelope approach we estimate stored 48 kg of CO_2 eq in total and hence less than 2kg of CO_2 equivalent per month (assuming a lifespan of two years).

emissions further. Another caveat, is that these calculations do not include CO_2 emissions and other environmental damages from recycling or disposing the solar light, as to our knowledge such assessments do not exist yet.

There are two differences between our sample and national averages that have important implications for these estimates. First, in our sample more households primarily use kerosene for lighting. While in our sample over 80% primarily rely on kerosene for lighting, it is only 35.0% of the country as a whole (KIHBS, 2018). Second, among households that rely on kerosene, more use tin lights as opposed to kerosene lanterns (KIHBS, 2018). In our sample 82.25% of households that used kerosene based lighting products in the past one month only used tin lamps, while 17.75% also used kerosene lanterns. For Kenya as a whole only 55.1% of households primarily use tin lamps, among those who use kerosene for lighting, and 44.9% kerosene lanterns.[19] Given that our sample is on average poorer and more rural and tin lights are cheaper to acquire and operate, this finding is not surprising. When we use the national averages instead of our data, we get to a cost of US $9.69 per ton of CO_2 equivalent (Appendix, Table A.3). However, these estimates assume that solar lights can be targeted at households that would otherwise use kerosene based products, which might not be trivial.

Cost estimates of the reduction of a ton of CO_2 equivalents can be compared with the social cost of carbon (SCC). SCC estimates vary as they depend inter alia on the rate used to discount future damages. The most recent central estimates of the U.S. Interagency Working Group on the Social Cost of Greenhouse Gases was US $50 per ton of CO_2 (Revesz et al., 2017; IWG, 2015). While the group was dismantled by the current U.S. administration Revesz et al. (2017) suggest that researchers and policy makers keep using this estimate until there are reliable up-dated estimates.

Our CO_2 abatement cost estimates of US $5.87 and US $9.69 can also be compared to the cost of other programs aiming to reduce CO_2 emissions. Abrell et al. (2017) estimates the cost for reducing one ton of CO_2 emissions through subsidies of solar in Europe between €500-1870 (US $600-$2244).[20] Gayer & Parker (2013) estimate the cost per ton of CO_2 averted in a subsidy program for electric cars between US $300-$1200. Davis, Fuchs & Gertler (2014) eval-

[19] KIHBS, 2018 households were asked about the lighting source they use primarily, whereby we used information about tin light and kerosene lantern use during the past month, hence the results are not exactly comparable.

[20] Using a conversion rate of 1 € =US $1.20 US

uate a large scale appliances replacement program in Mexico and estimate the cost per ton of CO_2reduced to be over US $500. Our estimates are higher than what Jayachandran et al. (2017) project based on an evaluation of a program which offered households in Uganda money to conserve trees on land that they own. Assuming that the observed effects persist with a permanent program, the authors estimate that the net present cost per ton of abated CO_2would be less than US $3.

Back-of-the envelope calculations suggests that if all households that use kerosene in Kenya for lighting (35.0% according to the 2015/2016 Kenya Integrated Household Budget Survey) had access to one solar light[21] and assume their kerosene reduction would be the same as in our study, this would lead to a reduction of 2.17 mega tonnes of CO_2 per year. This is equal to around 3.58% of Kenya's total greenhouse gas emissions and 11.14% of Kenya's energy emissions in 2014[22](Appendix, Table A.2). Assumptions for calculations are listed in Appendix Table A.1.

Previous studies also find an association between kerosene smoke and adverse health effects (Lam et. al, 2012; Furukawa, 2014; Kudo, Shonchoy & Takahashi, 2018; Pokhrel et al., 2010), in particular with regard to respiratory diseases and eye irritations. While there is a broad consensus that indoor air pollution is the most important environmental health risk factor worldwide (WHO, 2016), it is still unclear to what extent indoor kerosene lighting, as opposed to indoor biomass burning for cooking, is a relevant factor. Moreover, it remains unknown to what extent access to a solar light improves health outcomes – even if it leads to a reduction of indoor kerosene combustion as shown in the previous section. We use standardized questions from the European Community Respiratory Health Survey II to understand possible effects on respiratory symptoms and create an index following Bates et al. (2015) ranging from 0-5, where higher numbers indicate that the respondent suffers from more symptoms. For the questions related to eye health we also created an index based on six questions about symptoms for dry eyes, also following Bates et al. (2015). The questions that were used to create the index can be found in Appendix D.

We find a reduction in symptoms related to dry eye disease of about 0.48 symptoms for adults and for children (corresponding to 0.24 and 0.26 standard de-

[21]Again, here we assume that they only one solar light and, emissions could be further reduced if they get access to two lights.

[22]We are using the estimations from CAIT, 2017, as well as the latest Kenya Integrated Household Budget Survey from 2015/6.

viations and 16.7% and 19.5% reduction in symptoms respectively) and the difference is significant at the 5% level (Table 2.4, Columns 1 and 2). Children also face 0.39 fewer symptoms related to respiratory difficulties (significant at the 1% level and corresponding to 0.29 standard deviations and 28% reduction of symptoms compared to the control mean), whereby adults' reduction of 0.24 symptoms is not statistically significant (Table 2.4, Columns 3 and 4). Since children are the main users of the solar lights (as discussed in the next Section), it seems plausible that they experience somewhat stronger health effects. We also observe that women and girls are overall more likely to experience symptoms related to respiratory illnesses. Again this is not surprising, given that they tend to spend more time cooking, and hence are more exposed to emissions from wood-smoke.[23]

Table 2.4: Impact on Health

VARIABLES	(1) Adults Dry Eyes 0-6	(2) Pupils Dry Eyes 0-6	(3) Adults Respi. 0-5	(4) Pupils Respi. 0-5
Solar Works	-0.478**	-0.482**	-0.236	-0.392***
	(0.205)	(0.192)	(0.151)	(0.142)
Female	0.184	0.117	0.384***	0.167**
	(0.119)	(0.105)	(0.083)	(0.077)
Observations	1,313	1,202	1,313	1,202
R-squared	0.037	0.020	0.038	0.034
School FE	YES	YES	YES	YES
Controls	NO	NO	NO	NO
Control Mean	2.864	2.475	1.431	1.402
Number of Schools	20	20	20	20

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Indices are created based on European Community Respiratory Health Survey II and Bates et al. (2015). Higher numbers indicate that the respondent suffers from more symptoms.

In summary, solar lights are relatively inexpensive and considerably reduce kerosene use among households that previously primarily used kerosene for lighting. They therefore have the potential to reduce warming emissions at a cost

[23]Time use data from out survey data reveal that women and girls spend more time with household chores.

that is low compared with the social cost of carbon. Moreover, access to solar lights improves household members' health. In the next sections we discuss if, in addition to these environmental and health benefits, it also improves access to reliable energy services and allows households to lower energy expenditures.

2.5 Increasing Energy Access

Changes in Quantity and Quality of Light

Our survey data suggest that households with access to a functioning solar light used it frequently, namely for 6.1 out of 7 weekdays and for 3.51 hours the previous day on average. Sensor data confirm this finding. According to data from 220 sensors, 58.6% of households used the solar light on every day of the study; and on average households used the solar light for 4 hours per day. To calculate the number of hours that adults and children use lighting each day we also included questions about light use in the time use section of the survey. For every hour of the day, we asked respondents to report the primary activity they had engaged in. For every hour[24] without sunlight (6:00 pm to 7:00 am), we asked whether they used any lighting source, and if so, which one. From that information, we calculated the total number of hours per day that adults and children reported using any lighting source (i.e., total hours of lighting regardless of source used). Adults and children in the control households used an average of 3.3 and 3.2 hours of light per day (Table 2.5, Columns 1 and 2). Having a functioning solar light increases children's lighting hours by 0.38 hours (22.80 minutes) per day (Table 2.5, Column 1), corresponding to a 11.43 % increase in lighting hours. Solar lights do not have a statistically significant impact on lighting hours of adults (Table 2.5, Column 2).
In addition to more lighting hours, solar lights also increase the quality of light, in particular in comparison with tin lights (see Section 2.2.2). Solar lights also makes the supply of light more consistent. Respondents were 39.1 percentage-points less likely to sit in the dark over the last month and 64.9 percentage-points less likely to rely on a lighting source that is not their first choice because they ran out of kerosene or wick within the past month (Appendix, Table A.11).

Table 2.5: Impact on Light Use and Energy Expenditure

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Lighting Hours Children	Lighting Hours Adults	All- Energy Exp (KSH)	Energy Exp as Share of Total	Energy Exp as Share of Total w/o Edu
Solar Works	0.375***	-0.196	-115.781***	-0.027***	-0.034***
	(0.130)	(0.139)	(25.045)	(0.004)	(0.005)
Lower Bound 95%	-	-	-66.694	-	-
Upper Bound 95%	-	-	-164.868	-	-
Female	0.400***	0.084			
	(0.070)	(0.082)			
Observations	1,202	1,313	1,313	1,313	1,313
R-squared	0.109	0.021	0.054	0.096	0.077
School FE	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO
Control Mean	3.324	3.206	272.4	0.0510	0.0670
Number of Schools	20	20	20	20	20

Notes: Robust standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Solar ownership is instrumented with price discounts. We excluded education expenditure from Column 5, as school fees were due just before endline and are a large share of that month's expenditure.

Energy Expenditure Savings

An average household in the control group spends 272.40 KES (US $2.72) per month on energy.[25] Having a solar light allows households to reduce energy expenditure on average by 115.78 KES (US $1.16) per month (Table 2.5, Column 3), corresponding to 42.5% of household's total spending on energy. This is not surprising given that lighting is a large fraction of energy expenditure and that households replace on average one out of two solar lights (see also Table 2.3, Column 1). The amount households save, however, only corresponds to 2.4-3.3% of total cash expenditure (Table 2.5, Columns 4-5), because energy expenditures account for only a small fraction of total cash expenditure (5.1%).

These findings are likely to be a lower bound as kerosene prices were at a historic low due to falling global oil prices during our endline data collection in February 2016. According to the Kenyan Energy Regulatory Commission, pump prices for kerosene were 42.83 KES (US $0.43) per liter, while at baseline they were 64.92 KES (US $0.65) per liter.[26] This baseline price (July/August 2015) is similar to the average kerosene price in the year before our study took place (July 2014 - July 2015).[27] In Kenya, as in other countries in sub-Saharan Africa, kerosene prices in rural and remote areas are much higher than at the pump stations in the city center due to high transportation costs and lower quantities being sold (Lighting Africa, 2012)

With a monthly interest rate of 7.5%, which is most common in Kenya,[28] monthly breakages of 1.15%, which we observed in our data[29] and assuming that the lights last a maximum of two years, we obtain a net present value (NPV) for the smaller solar light (Sun King Eco) of 246.42 KES (US $2.46). The amortization period (i.e. NPV=0) (with 7.5% interest rate, and 1.15%

[24] We asked for half-hour slots in the evening between 7pm and 10pm, where we expected most use based on answers from the pilot study.

[25] Spending on kerosene was lower than in the beginning of the study due to lower kerosene prices. Total expenditure on the other hand were higher due to school fees, which were due shortly before data collection and possibly also since the endline happened was right after harvest, while baseline was before harvest.

[26] http://www.erc.go.ke/index.php?option=com_content&view=article&id=162&Itemid=666 However, pump prices differ a lot from the prices people face in remote areas (see Lighting Africa (2012)).

[27] ERC (2015) provides information on three price points (July 14, Feb 15, and Jun 15). The average of these three points is 66.09 KES (Nairobi) and 69.54 KES if adjusted for Busia.

[28] This is the interest rate offered by the mobile money provider MPESA to households that do not have a bank account. More information can be found on www.safaricom.co.ke.

[29] We observed a total breakage rate of 7.78% and assume breakages are evenly distributed over time

monthly breakages) is 14 months (Table 2.6, Row 1). According to our calculations, the investment in a solar light pays of over a period of two years if a household saves more than 86.20 KES (US $0.86) per month with a solar light, which is likely. Hence in addition to environmental and health impact, households save 2.7% of their monthly cash expenditure and the investment pays off after 14 months. However, breakage rates remain an issue and risk averse households might not want to invest into an appliance that breaks down with a likelihood of 7.8% within the first seven months. Table 2.6 Row 2 shows calculations with a lower interest rate of 4% per month, which is what is offered to households in rural Kenya that have a bank account.[30]

Table 2.6: Net Present Value (NPV) and Amortization

Assumptions			NPV			Amortization		
	Breakages %	Interest Rate %	Mean KES	Lower Bound KES	Upper Bound KES	Mean Months	Lower Bound Months	Upper Bound Months
			115.78	66.69	164.86	115.71	66.69	164.86
1	1.15%	7.5%	246.42	-136.90	986.42	14	n/a	7
2	1.15%	4.0%	665.50	75.41	1'511.00	11	21	7

Notes: Our results are based on our point estimate and a 95% CI around as upper and lower bounds (Table 7, Column 1). Breakage rates of 1.15% are based on our data and we assume that breakage rates are distributed evenly across time. Interest rates of 7.5% are based on figures based on credits available for people without bank accounts (M-shwari) and 4% are for those with a bank account (KCB M-PESA). Interest rates are from 2018. We assumed the solar lights would last a maximum of two years, as this is the lenght of the warranty of the product.

As explained in Section 2.2.2, half of the group receiving a free solar light was given a Sun King Eco (SK Eco) and the other half a Sun King Mobile (SK Mobile) solar light. The SK Mobile has a larger and stronger light and the ability to charge a mobile phone. Households which received an SK Mobile reduce their mobile phone charging costs (19.90 KES or US $0.20) per month, which corresponds to an almost 100% reduction compared with the control group's expenditure. Otherwise, however, they do not save more than households receiving a smaller light (regression results are available from the authors on request). Given the much higher purchasing price of 2'400 KES (US $24.00) the Net Present Value (NPV) is only -1'191.14 KES (- US $11.91), if we assume 7.5%

[30]More information about interest rates for different credit products commonly used in the study region can be found on www.safaricom.co.ke.

monthly interest rate, 1.15% monthly breakage rate, and a maximum life-time of two years.

An additional possible private return is a reduction in travel time to purchase kerosene. However, we do not expect time use savings to be large, as most households still use kerosene once they get access to a solar light. They typically only purchase kerosene six times per month and most (89.7%) would undertake the trip to the market center/petrol station in any case for other reasons.

Educational Outcomes

There is a wide held belief among practitioners in the solar field that solar lights will improve children's school outcomes. Some companies even sell solar lights through head teachers of primary schools using that reason (SolarAid, 2013). The idea is that better quality lighting and additional lighting time will allow children to study more and/or under better conditions at home.

Children in all types of households received homework on 2.6 days during the previous week and completed the homework after dark most of the time. Having access to a functioning solar light increased the share of homework completed after dark by 10.0 percentage-points (Table 2.7, Column 2) and increased self-reported homework completion by 15.9 percentage-points (Table 2.7, Column 1). However, we do not find any changes in hours spent on homework or in school (Table 2.7, Columns 3 and 4) or test scores (Table 2.8, Columns 1-6). Moreover, we find that sleeping hours are reduced by 0.70 hours (or 42 minutes) (Table 2.7, Column 5), which could adversely affect children's school performance.

Previous literature also did not find effects of accessing solar on test scores (Furukawa, 2013; Kudo, Shonchoy & Takahashi, 2017). Hassan & Lucchino (2016) also did not find that test scores change at the individual level. The authors suggest, nevertheless, that there were effects at the class level. However this analysis was not part of their initial research plan and has, as the authors admit, some identification challenges. One might still be puzzled that children report increases in homework completion but we do not observe any changes in their test scores. Children's self-reported increase in homework completion might simply be driven by social desirability bias (which is likely given that they do not seem to spent more time on homework). Or, the increase in completion might be real but homework completion does not lead to better learning and/or test scores. It is also possible that we do not see any changes in test scores since not enough time has lapsed between the beginning and the end of the study. Finally, spillover effects with children from the control group benefitting from children who received or purchased a solar light might lead to null results, which will be discussed in Section 2.6.3.

Table 2.7: Impact on Homework Completion and Time Use

VARIABLES	(1) Home -work Completion	(2) Share HW after Dark	(3) Home -work (hours)	(4) School (hours)	(5) Sleep (hours)
Solar Works	0.159***	0.100***	0.282	0.475	-0.702***
	(0.049)	(0.039)	(0.183)	(0.322)	(0.227)
Pupil Female	-0.028	0.010	-0.085	-0.062	-0.233*
	(0.027)	(0.022)	(0.098)	(0.178)	(0.120)
Observations	1,050	1,050	1,202	1,202	1,202
R-squared	-0.003	-0.002	0.044	0.010	0.019
School FE	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO
Control Mean	0.692	0.780	2.458	4.508	8.077
Number of Schools	20	20	20	20	20

Notes: Robust standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Solar ownership is instrumented with price discounts. Column 1 shows the share of times the pupil was able to complete the homework past week. Column 2 shows the share of times the homework was completed after dark. Columns 2-5 show data from the time use section. In this table we control for pupil's class and gender.

Table 2.8: Test Scores

VARIABLES	(1) Swahili	(2) Math	(3) English	(4) Science	(5) Average	(6) KCPE Average
Solar Works	-0.161	0.017	-0.047	-0.037	-0.088	-0.137
	(0.099)	(0.100)	(0.086)	(0.093)	(0.076)	(0.162)
Pupil Female	0.193***	-0.063	0.082*	-0.089*	0.043	0.002
	(0.049)	(0.052)	(0.044)	(0.048)	(0.039)	(0.080)
Observations	1,082	1,095	1,082	1,099	1,101	226
R-squared	0.355	0.286	0.467	0.372	0.616	0.507
School FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Control Mean	0	0	0	0	0	0
Number of Schools	20	20	20	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Test scores are from final yearly exam in March 2016 and standardized. We control for pupils' class and gender as well as baseline test scores from March 2015. The last column contains the average of class eight who attended KCPE exam, an exam held nationally in the end of primary school.

2.5.1 Effects of Subsidies on Demand and Use

Given that solar lights can reduce harmful and warming emissions at a low cost and have additional private benefits, increasing their adoption could be in the public interest. Therefore we are interested in learning about how further price reductions (either through subsidies or further technological progress) effects demand, and use, and whether and how other measures such as decreased transaction costs and information can increase take-up of solar lights, which was at 6.5% during baseline.

Effects of Subsidies on Demand

Demand responds strongly to price changes. We start by looking at the share of people who took up the offer we made to purchase or receive a solar light within our sample. While everyone in the free group took up the offer of a solar light as well as 68.8% of those who could purchase a solar light at 400 KES (US $4), take-up decreased to 37.4% when the offer was to purchase a light for 700 KES (US $7). At market price of 900 KES (US $9) 28.9% bought the solar light (Table 2.9, Column 1). This corresponds to an average price elasticity of demand of -1.07, meaning that a 1% increase in price leads to a 1.07% reduction in quantity that is purchased (Table 2.9, Column 4).

We also analyze the share of households that owned a solar light seven months after baseline, independently from whether they redeemed the voucher they received from us or purchased it in some other way (Table 2.9, Column 2). These measures are generally larger than the first column, as people could also purchase solar lights outside of our study and some households already owned one at baseline. Using this measure, there is no statistical difference between the highest (US $9) and the second highest price (US $7) (Table 2.10, Column 2 and 3). Our data suggest that breakages were common, particularly for solar lights with sensors. Breakage rates for solar lights without sensors were still at 7.78% after seven months.

Interestingly, whereas 44.6% of those who received an offer to purchase a solar light at market price owned a solar light at endline, only 19.1% in the control group owned one (Table 2.9, Column 2). This could be caused by a number of reasons, such as increased information about solar lights in our US $9 treatment group, as the field staff showed them the product and explained its basic features (see script in the Appendix). Moreover, the program reduced transaction costs, since the solar lights were available through the head teacher in their children's school, whereas in the control group respondents had to buy them elsewhere. In fact, 31.3% of respondents in the control group mentioned that they never saw a solar light before and only 8.5% said that solar lights could be bought in their own village. The remaining respondents mention that they either had to travel to the closest town or market center (45.8%) or even to a larger city to buy a solar light (14.4%).

Together these findings suggest that while reducing transaction costs and increasing information can increase take-up, further price reductions are needed to boost adoption above 50%. In fact, substantial price reductions are needed as a reduction to US $7 did not lead to higher ownership at endline (compared with the market price of US $9).

Table 2.9: Solar Light Ownership at Endline

	(1)	(2)	(3)	(4)
VARIABLES	Redeemed Voucher	Solar Ownership	Ownership (works)	Log Quantity
Free	1.000	0.974***	0.834***	
	(0.000)	(0.008)	(0.019)	
Voucher 400 KES	0.688***	0.734***	0.683***	
	(0.032)	(0.031)	(0.033)	
Voucher 700 KES	0.374***	0.437***	0.383***	
	(0.035)	(0.037)	(0.036)	
Voucher 900 KES	0.294***	0.446***	0.397***	
	(0.033)	(0.037)	(0.036)	
Control	0.000	0.191***	0.172***	
	(0.000)	(0.021)	(0.020)	
Log Price				-1.071**
				(0.039)
Observations	1,396	1,313	1,313	
R-squared	0.805	0.738	0.643	0.997

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Column 1 shows whether respondents purchased a solar light through our program. Column 2 shows solar light ownership at endline and Column 3 shows ownership of a functioning solar light at endline.

Effects of Subsidies on Use

In this section we study whether those receiving a free solar light use it less than those who paid for it.[31] There could be differential use of solar lights between buyers and those who received a solar light for free for two main reasons. First, there could be a selection effect: households that purchase a solar light might be different from households how decide not to. For example, lower lighting needs might make some households less likely to buy solar lights. Second, there might be a sunk cost effect, whereby the act of paying a price for a solar light makes households more likely to use it. While our research design does not enable us to differentiate between the selection and the sunk cost effect, we can test whether households, that purchase a solar light use it more than those who received it for free.

Table 2.10: Buyers vs. Non-Buyers

VARIABLES	(1) Hours Used Yesterday	(2) Energy Spending (KES)	(3) Lighting Hours Pupils	(4) Lighting Hours Adults	(5) Time Spent Homework (Hrs)
Buyer vs. Free	0.099	26.849	-0.021	0.140	-0.055
	(0.201)	(22.619)	(0.130)	(0.140)	(0.095)
Observations	423	424	388	424	388
R-squared	0.001	0.003	0.000	0.002	0.001
School FE	NO	NO	NO	NO	NO
Controls	NO	NO	NO	NO	NO
Free Mean	3.069	6.028	3.544	3.086	0.786

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Sample restricted to owners of functioning Sun King Eco Light.

Using a similar approach to Dupas & Cohen (2010), we limit the sample to households that had a functioning solar light at endline,[32] and test whether households that bought a solar light use them more. We chose to combine the offers into one as our power to detect any differences would be very low otherwise. We find that households that received a free solar light use it as

[31] We chose to combine the offers into one, since sample sizes in each cell would become very small when reporting each price point. There is also no difference in use when looking at each offer individually (regression results are available from the authors on request).

[32] The main result does not change significantly if the sample is only restricted to those who still own a solar light at endline no matter if it still worked or not.

frequent as households that purchased it (Table 2.10, Column 1). There is also no difference in reduction in energy expenditure (Table 2.10, Column 2), nor in lighting hours for adults or children (Table 2.10, Column 3-4), hence we do not find any evidence that price affect use of solar lights.

2.6 Robustness Checks

2.6.1 Attrition

Despite our efforts to keep attrition low, attrition was at 4.5% in the free group, 5.7% in the voucher group and 7.8% in the control group among the adult respondents. Attrition among pupils was higher at 10.5%, 7.2% and 8.5% respectively (Appendix, Table A.4). Attrition does not correlate with the observable characteristics we tested for (Appendix, Table A.5). However, attrition is still a concern as the attritors may be different from the non-attritors in some unobservable dimensions, which may correlate with our outcomes of interest. We address this concern using a bounding approach developed by Lee (2005) and commonly used since. We trim the outcome variable of interest in the free group (since this is the group with less attrition), either chopping off the observations with the highest or the lowest values, so that the number of observed individuals is the same in both groups. This means that we make extreme assumptions about the missing information. For all estimates, the lower and upper bounds do not change signs, which indicates that the results are robust to attrition (Table 2.11).

Table 2.11: Lee Bounds

	(1) Ker Use (l)	(2) Engery Exp. (KES)	(3) Dry Eyes Adults	(4) Dry Eyes Pupils	(5) Respiratory Pupils	(6) Light Hours Pupil	(7) Sleep Time Pupil	(8) HW Completion Pupil
Point estimate	-0.911***	-74.812***	-0.159**	-0.194**	-0.165*	0.237**	-0.392***	0.099***
Lower Bound	[-1.219	[-104.820	[-0.426	[-0.196	[-0.164	[0.179	[-0.475	[0.086
Upper Bound	-0.858]	-68.294]	-0.158]	-0.152]	-0.152]	0.262]	-0.276]	0.140]
Total Sample	800	800	800	800	800	800	800	800
Non-Missing	740	747	747	737	737	737	737	647

Notes: Lee bounds in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

2.6.2 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 (or type I errors) (Benjamini, Krieger & Yekutieli, 2006; Anderson, 2008). In Table 2.12, Column 2 reports intention to treat (ITT) estimates of our main results alongside with adjusted q-values. We report ITT estimates, since this is what we pre-specified in our pre-analysis plan. As expected the ITT coefficients are smaller than the treatment effect on the treated (TOT) estimates. The false discovery rate adjusted q-values are robust to multiple hypothesis testing (Table 2.12, Column 5).

2.6.3 Spillovers

We could underestimate the impacts of having access to solar if households which receive a free solar light or purchase one share them with households in the control group of the same school. 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 individual household members from control households visit households with a solar light to enjoy their improved lighting. Finally, it could be that children in the control group benefit from the schooling progress of their peers who have access to a solar light. We look at spillovers in different ways. First, we report the answers we asked children and adults about borrowing, lending and sharing the solar light as well as if children brought them to school and shared it there. Second, we use an approach that is similar to Baird et al. (2014) and Kudo, Shonchoy & Takahashi (2017), whereby the treatment saturation can be used to estimate spillover effects on the non-treated population.

Only 14 households (2.2%) that received or purchased a solar light through our program shared the light with someone from the same school and they shared it only 1.4 times on average during the past month. It is therefore very unlikely that there are significant spillovers from borrowing or lending the solar light. We also asked children with whom the solar light was shared, when they used it most recently. While many shared it with other household members, only 11 pupils (2.3 %) shared it with someone from the same school. Hassan and Lucchino (2016) hypothesize that they find spillover effects, probably from sharing solar lights in schools (see Section 2.5). In our sample however, bringing the solar

Table 2.12: Intention to Treat and Adjustments for Multiple Hypothesis Testing

		Control [SD] (1)	ITT (SE) (2)	TOT (SE) (3)	P-Val (4)	FDR q-val (5)
(1)	Ker. Use (l)	2.445	-0.911***	-1.470***	0.000	0.001
		[2.868]	(0.177)	(0.259)		
(2)	Energy Exp.(KES)	272.354	-74.812***	-115.781***	0.000	0.001
		[279.328]	(13.747)	(25.045)		
(3)	Nr. Ker. lights used	2.234	-0.687***	-1.027***	0.000	0.001
		[1.094]	(0.075)	(0.109)		
(4)	Dry Eyes Pupils (0-6)	2.475	-0.355**	-0.482**	0.012	0.010
		[1.831]	(0.141)	(0.192)		
(5)	Dry Eyes Adults (0-6)	2.864	-0.323**	-0.478**	0.020	0.011
		[1.999]	(0.123)	(0.205)		
(6)	Respirat. Pupils (0-5)	1.402	-0.220*	-0.392***	0.006	0.007
		[1.363]	(0.127)	(0.142)		
(7)	Respirat Adults (0-5)	1.431	-0.131	-0.238	0.117	0.031
		[1.467]	(0.079)	(0.150)		
(8)	Light Use Pupil	3.323	0.263**	0.375***	0.004	0.006
		[1.325]	(0.088)	(0.130)		
(9)	Light Use Adult	3.206	-0.138	-0.196	0.159	0.039
		[1.439]	(0.110)	(0.139)		
(10)	Sleep Time Pupils (hrs)	8.077	-0.391**	-0.716***	0.001	0.003
		[2.046]	(0.137)	(0.209)		
(11)	HW Time Pupils (hrs)	2.458	0.181	0.278	0.115	0.031
		[1.670]	(0.129)	(0.176)		
(12)	HW Completion (%)	0.692	0.097***	0.160***	0.001	0.003
		[0.462]	(0.023)	(0.048)		
(13)	HW Completion (%) after Dark	0.780	0.059**	0.106***	0.006	0.007
		[0.356]	(0.028)	(0.039)		

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table includes main outcomes from the study. We controlled for school fixed effects and gender when we looked at individual outcomes. No other control variables are used. Column 1 reports the mean from the control group with SD in brackets. Column 2 reports ITT regression with robust standard errors in parentheses (sample is restricted to free group and control group). Column 3 reports IV estimates with robust standard errors in parentheses. Column 4 shows standard p-values for TOT estimates. Column 5 reports the FDR-adjusted q-values following Benjamini, Krieger & Yekutieli (2006) associated with the p-values in Column 4.

light to school was very rare as only 19 children had ever taken the solar light to school. Again, it does not seem plausible that this led to large spillover effects. The number of people in one's neighborhood (radius of 500 m) who received a free solar light varies between the different households and we use this variation to see whether control households that happen to live close to a large number of households that received a free solar light are benefiting from these lights. As outcome variables we use hours energy spending, lighting hours for pupils and adults as well as time spent doing homework. We choose these variables since we consider them "first stage", meaning that it is unlikely that the other outcomes change if this outcome does not change. None of these outcomes of the control group changes for households that have a higher share of neighbors who received a free solar light (Table 2.13, Columns 1-4). From this additional analysis we conclude that while we can not rule out that spillover effects exist to some extent, it is unlikely they lead to a large underestimation of effects in our study.

Table 2.13: Spillover Use

VARIABLES	(1) Energy Spending (KES)	(2) Lighting Hours Pupils	(3) Lighting Hours Adults	(4) Time Spent Homework (Hrs)
# Neighbours (Free) within 500m	-10.087	-0.014	-0.056	-0.049
	(7.251)	(0.049)	(0.052)	(0.032)
# Neighbours within 500m	5.671	-0.001	0.005	0.015
	(4.010)	(0.021)	(0.015)	(0.016)
Observations	368	339	368	334
R-squared	0.005	0.003	0.009	0.013
School FE	YES	YES	YES	YES
Controls	NO	NO	NO	NO
Mean	272.1	3.324	3.207	0.670
Number of Schools	20	20	20	20

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Sample restricted to control group.

2.7 Conclusion

There is a heated debate about how societies should increase energy access while maintaining environmental sustainability. This is particularly relevant in emerging economies where the largest increase in energy demand and in CO_2 emissions will come from. There are high hopes for novel technologies that increase energy efficiency and the use of renewable energies. The idea is that these technologies can create "win-win" cases where both society at large wins due to lower emissions and pollution and the consumer wins due to lower costs or better energy access. However recent impact evaluations, primarily from high-income countries, show that the potential for such "win-win" cases might be much more limited than previously thought (Davis, Martinez & Taboada, 2018; Hanna, Duflo & Greenstone, 2016, Davis, Fuchs & Gertler, 2014; Fowlie, Greenstone & Wolfram, 2018; Allcott & Greenstone, 2012).

We provide evidence for such a double win case in a developing country context. Solar lights are used as a substitute for kerosene and thus reduce kerosene related emissions, which has benefits that are, in part, external to the household. This finding has at least two important aspects. First, environmental externalities: kerosene combustion emits a high concentration of Black Carbon, which is around 700 times more warming than CO_2. Having a functioning solar light leads to a reduction in emissions equivalent to 828.47 kg of CO_2 per household yearly, and if scaled to the whole country, the reduction would correspond to 3.58% of Kenya's greenhouse gas emissions in 2014 at a cost of less than US $10 per ton of CO_2. This cost is low compared with the estimated social cost of carbon of US $50 per ton of CO_2 (Revesz et al., 2017; IWG, 2015) as well as when compared to other programs aiming to reduce emissions with increase efficiency or reliance on renewable energies in Mexico (Davis, Fuchs & Gertler, 2014), Europe and the US (Abrell et al., 2017). Second, accessing solar lights reduced symptoms related to asthma and dry eyes disease, especially for children, who are also the main users of the solar light. This is in line with a number of studies that find improvements in indoor air-quality and a reduction in symptoms related to eye and respiratory illnesses (Furukawa 2013; Barron & Torero, 2017; Grimm et al., 2016 a). It also corresponds to the findings of Kudo, Shonchoy & Takahashi (2018) with regard to eye irritation, however, they did not find any effects on respiratory symptoms.

Solar lights also provide access to better and more consistent light quality and allow households to reduce 2.7-3.4% of total monthly expenditure. There seems to be converge on these figures among different studies: Grimm et al. (2016a) discovered expenditure reduction of US $0.92 as a result of providing solar lights for free, corresponding to 3% of total expenditure in Rwanda. Kudo, Shonchoy & Takahashi (2017) in their study in Bangladesh, calculate expenditure savings of 3.2% of total expenditure,[33] Aevarsdottir et al. (2017) report that households in Tanzania were able to cut their lighting expenditure in half, which is also similar to what we find. From a typical households' perspective purchasing a small solar light pays off within the first 14 months from a purely financial perspective. However an average household cannot recoup the cost of the larger Sun King Mobile light as they would have to save more than US $2.30 per month. Even for the smaller light, the amortization periods are still relatively long at current prices. Given this fact, it is unsurprising that take-up increases sharply with price reductions, ranging from 29% at market prices (US $9) to 69% when sold at the lowest price (US $4). We do not observe that solar lights are used less when prices decrease.

Together these results suggest that price reductions are likely to increase product take-up and also use, reducing kerosene use and related emissions, which has health and environmental benefits that are larger than their social cost. Moreover it increases access to some sort of basic modern energy, which is an important policy goal for the United Nations as well as many national governments, and, at least in the medium run might be more cost-effective in this rural setting than grid extension (Lee et al 2016b).

Solar lighting is however not a panacea to address energy poverty and climate change. While they provide some improvement compared with kerosene, energy access is still limited to lighting and mobile phone charging in the case of the larger version of the light and does not allow households to power appliances like fans or irons. Solar lights will not be enough as living standards rise. Moreover, cookstoves, not kerosene lights, are the most important contributor to indoor air pollution, and a better cooking solutions must be found, to achieve substantial health gains (WHO, 2016). Also, while every reduction in warming emissions counts, the contribution of kerosene lights remains limited. Moreover, 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, Peters & Sievert, 2017). Hence the counterfactual might look different

[33] This is only significant at the 10% level. However, it is only 1.6% of total expenditure, which is not significant at the 10% when they do control for baseline.

in the future. Finally, maintenance and recycling of old solar lights, especially their batteries still remains a challenge and if not solved properly might create new environmental challenges.

First and foremost we hope that future research will rigorously field test and evaluate approaches that aim to improve energy access as well as energy efficiency and the use of renewable energies in developing countries. This will allow policy makers to compare the cost-effectiveness of different policy options in low-income settings. It is particularly relevant to study policy options in developing countries as this is where energy demand and CO_2 emissions are projected to grow most significantly in the coming years. With regard to solar lighting in particular, we hope that future studies will evaluate demand and impacts in environments where kerosene is not the counterfactual (anymore), as large shares of the population are electrified or use battery powered torches rather than kerosene lights. It would also be important to further analyze what drives and constraints different types of consumers' demand for such products and wether there are important market failures in contexts that are different from ours. Further, we hope that researchers will look at the problem of electronic waste in developing countries and how it can be addressed. Finally, for our findings with regard to 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 improve indoor air quality.

2.8 Appendix

A. Information About Design, Intervention & Calculations

Table A.1: Assumptions and Sources for CO2eq Calculations

	Unit	Amount	Source
Total Emissions (2010)	MtCO2eq	60.53	CAIT, 2017
Energy Emissions	MtCO2eq	19.47	CAIT, 2017
Using Kerosene	%	35.0	2015/2016 Kenya
Of which using Tins	%	55.1	Integrated Household Budget Survey
Of which using Hurricanes	%	44.9	(KHBS 2015/6)
Tins CO2eq Kerosene/kg	kg	65.77	Lam et al. (2012b)
Hurricanes CO2eq Kerosene/kg	kg	9.38	
Total HH in Kenya	#	12'115'000	
Total Pop Kenya	#	48460000	World Bank 2016
People per HH in Kenya	#	4	KHBS 2015/16
CO2eq Discount Rate	%	3	Greenstone, Kopits, Wolverton (2011)
Embedded CO2 in Production	kg	48	Alstone et al. (2014)
Density of Kerosene	kg/l	0.8	total.co.ke (2018)
Tins CO2eq Kerosene Reduction per HH/month	kg	0.97	Our Data
Hurricanes CO2eq Kerosene Reduction per HH/month	kg	1.45	Our Data

Table A.2: Cost per Ton of CO2eq and Impact on National Emissions

Our Study					
	Unit	Amount	Lower Bound	Upper Bound	Notes
Reduction in CO2eq 2yrs per HH	kg	1'334.23	993.823	2'167.900	Discounted 3% per yr 1.15% breakages per month Share of Tins: 73.7 %
Cost per HH for 2yrs	$	9			Current market price
Cost per Ton of CO2eq	$	5.87	9.06	4.15	
Projections if Scaled Nationally					
Reduction in CO2eq 2yrs per HH	kg	929.23	492.53	1462.55	Discounted 3% per yr 1.15% breakages per month Share of Tins: 55.1 %
Cost per HH for 2yrs	$	9			Current market price
Cost per Ton of CO2eq	$	9.69	18.27	6.15	
Projections as % of Kenya's Total Emissions in 2014					
Total CO2eq reduced year	Mt	2.17	1.09	3.25	
Share of Total Emissions in 2014	%	3.58	1.81	5.36	Total emissions 61.53 MtCO2eq CAIT, 2017
Share of Energy Emissions in 2014	%	11.14	5.61	16.67	Total emissions 19.47 MtCO2eq CAIT, 2017

Notes: Failure rate of 1.1% is based on a total failure rate of 7.78% in our sample across 7 months. We assume that failure rates remain the same for 24 months, after which none of the solar lights works anymore. All other assumptions are listed in A.1.

Table A.3: Sampled Households by School

School Name	Frequency
Malanga	70
Lwanyange	70
Emukhuyu	70
Esidende	70
Maolo	70
Sianda	80
Khayo	80
Sango	40
Opeduru	75
Mwangaza	70
Olepito	75
Obekai	75
Kaliwa	75
Kamarinyang’	75
Ong’aroi	75
Asing’e	75
Ng’elechom	75
Akites	70
Aburi	50
Odiyoi	70
Total	1,410

B. Additional Robustness Checks

Table A.4: Attrition

VARIABLES	(1) Attrition (Adults)	(2) Attrition (Pupils)
Free Solar Light	-0.033*	-0.013
	(0.017)	(0.019)
Voucher	-0.021	0.020
	(0.016)	(0.019)
Observations	1,396	1,396
R-squared	0.003	0.002
Control Mean	0.0780	0.0850

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Correlation of Attrition with Observable HH Characteristics

VARIABLES	(1) Endline Completed	(2) Endline Completed	(3) Endline Completed	(4) Endline Completed	(5) Endline Completed	(6) Endline Completed	(7) Endline Completed	(8) Endline Completed.	(9) Endline Completed
Iron Roof	0.001								
	(0.013)								
HH Head Female		-0.002							
		(0.013)							
Household Size			0.005						
			(0.003)						
Main Income is Agriculture				0.015					
				(0.015)					
Business Ownership					0.014				
					(0.012)				
Yrs of Schooling HH Head						-0.000			
						(0.002)			
Number of Mobile Phones							0.002		
							(0.009)		
Solar Lantern Ownership								0.006	
								(0.019)	
Access to Electricity									0.011
									(0.040)
Observations	1,396	1,396	1,396	1,396	1,396	1,332	1,395	1,396	1,396
R-squared	0.000	0.000	0.002	0.001	0.001	0.000	0.000	0.000	0.000
School FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO	NO	NO	NO	NO
Control Mean	0.917	0.917	0.917	0.917	0.917	0.917	0.917	0.917	0.917
Number of Schools	20	20	20	20	20	20	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Impact on Kerosene Use and Emissions- With Controls

VARIABLES	(1) Nr of Kerosene Lights (kg)	(2) Used Ker Yest.	(3) Tins Kerosene Use (l)	(4) Lantern Kerosene Use (l)	(5) Monthly Kerosene Use (l)	(6) Monthly PM 2.5 (g)	(7) Monthly BC (g)	(8) Monthly CO2eq (kg)
Solar Works	-0.997***	-0.292***	-1.204***	-1.736***	-1.438***	-95.948***	-92.320***	-67.883***
	(0.104)	(0.037)	(0.312)	(0.398)	(0.256)	(18.278)	(17.681)	(12.927)
Observations	1,313	1,313	957	342	1,299	1,291	1,291	1,291
R-squared	0.188	0.205	0.062	0.272	0.087	0.080	0.080	0.080
School FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Control Mean	2.234	0.837	2.502	2.265	2.445	164.9	158.8	158.8
Number of Schools	20	20	20	20	20	20	20	20

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Column 1 shows the reduction for households that only own tin lights, Column 2 for everyone else. Columns 3-8 show information for both types of households. In Column 3-6 we used the following factors: if HH used tin lanterns only 90g of BC/kg of Kerosene, 93g of PM2.5/kg of Kerosene and 2770g of CO2eq/kg of Kerosene. If the household only used kerosene lanterns 9g of BC/kg of Kerosene, 13g of PM2.57kg of Kerosene and 3080 g of CO2eq7kg of Kerosene. All factors are based on Lam et al. (2012). The 13.79

Table A.7: Impact on Health- With Controls

VARIABLES	(1) Adults Dry Eyes 0-6	(2) Pupils Dry Eyes 0-6	(3) Adults Respi. 0-5	(4) Pupils Respi. 0-5
Solar Works	-0.472**	-0.487**	-0.235	-0.393***
	(0.203)	(0.190)	(0.149)	(0.142)
Female	0.195	0.114	0.396***	0.168**
	(0.120)	(0.105)	(0.084)	(0.077)
Observations	1,313	1,202	1,313	1,202
R-squared	0.040	0.024	0.042	0.036
School FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Control Mean	2.864	2.475	1.431	1.402
Number of Schools	20	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Control variables include electricity connection at baseline, business ownership, whether anyone in the household was employed during the past 12 months and household size.

Table A.8: Impact on Light Use and Energy Expenditure - With Controls

VARIABLES	(1) Lighting Hours Children	(2) Lighting Hours Adults	(3) All- Energy Exp (KSH)	(4) Energy Exp as Share of Total	(5) Energy Exp as Share of Total w/o Edu
Solar Works	0.379***	-0.177	-113.671***	-0.028***	-0.034***
	(0.129)	(0.136)	(24.193)	(0.004)	(0.005)
Female	0.403***	0.102			
	(0.070)	(0.082)			
Observations	1,202	1,313	1,313	1,313	1,313
R-squared	0.113	0.048	0.093	0.102	0.078
School FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Control Mean	3.324	3.206	272.4	0.0510	0.0670
Number of Schools	20	20	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Control variables include electricity connection at baseline, business ownership, whether anyone in the household was employed during the past 12 months and household size.

Table A.9: Impact on Homework Completion and Time Use- With Controls

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Home -work Com- pletion	Share HW after Dark	Home -work (hours)	School (hours)	Sleep (hours)
Solar Works	0.159***	0.099**	0.293	0.479	-0.709***
	(0.049)	(0.039)	(0.182)	(0.321)	(0.227)
Pupil Female	-0.029	0.009	-0.081	-0.063	-0.234*
	(0.027)	(0.022)	(0.098)	(0.178)	(0.120)
Observations	1,050	1,050	1,202	1,202	1,202
R-squared	-0.003	0.002	0.050	0.011	0.021
School FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Control Mean	0.692	0.780	2.458	4.508	8.077
Number of Schools	20	20	20	20	20

Notes: Robust standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Solar ownership is instrumented with price discounts. Column 1 shows the share of times the pupil was able to complete the homework past week. Column 2 shows the share of times the homework was completed after dark. Columns 2-5 show data from the time use section. In this table we control for pupil's class and gender. In this table we control for pupil's class and gender in addition to standard controls, namely electricity connection at baseline, business ownership, whether anyone in the household was employed during the past 12 months and household size.

C. Additional Outcomes

Table A.10: Time Use Adults

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Sleep	Chores	Recreation	Work	Ag Work	Non-Ag Work	Work after dark
Solar Works	0.200	0.110	0.838	-1.414**	-0.786	-0.567	-0.761**
	(0.460)	(0.354)	(0.563)	(0.698)	(0.541)	(0.671)	(0.324)
Solar Works * Female	-0.544	-0.551	-0.416	1.683**	0.787	0.897	1.079***
	(0.554)	(0.491)	(0.661)	(0.801)	(0.615)	(0.749)	(0.372)
Female	0.040	5.252***	-1.696***	-3.360***	-1.764***	-1.573***	-1.599***
	(0.318)	(0.284)	(0.380)	(0.465)	(0.368)	(0.440)	(0.216)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.001	0.471	0.088	0.090	0.045	0.026	0.066
School FE	YES	YES	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO	NO	NO
Control Mean Male	6.909	1.273	4.746	6.064	3.735	2.307	2.587
Number of Schools	20	20	20	20	20	20	20

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Solar ownership is instrumented with price discounts.

Table A.11: Light Interruptions

VARIABLES	(1) Light Interruption Dummy	(2) Light Interruption	(3) Use Alternative Dummy	(4) Use Alternative
Solar Works	-0.391***	-1.219***	-0.357***	-0.649***
	(0.043)	(0.141)	(0.045)	(0.138)
Observations	1,286	1,286	1,286	1,285
R-squared	0.154	0.109	0.047	0.013
School FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Control Mean	0.445	1.153	0.402	0.815
Number of Schools	20	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Questions about light interruption and use of alternative lighting sources were asked for the past month.

Table A.12: Perceived Safety at Night

VARIABLES	(1) Feeling Safe at Night Home	(2) Feeling Safe at Night Outside	(3) Burns past 3 months
Solar Works	-0.041	-0.045	-0.006
	(0.050)	(0.047)	(0.013)
Female	-0.119***	-0.130***	0.005
	(0.029)	(0.028)	(0.007)
Observations	1,313	1,313	1,313
R-squared	0.053	0.041	0.010
School FE	YES	YES	YES
Controls	NO	NO	NO
Control Mean	0.512	0.357	0.0190
Number of Schools	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Question asked: In the last 7 days how often did you feel safe at your house (outside of the house) at night? 1=always 0= usually, sometimes or never.

Table A.13: Impact on Psychological Outcomes

VARIABLES	(1) Future Better than Parents (0-3)	(2) Econ Sit Improved (0-4)	(3) Future holds good things (0-3)	(4) Happiness (0-3)	(5) Life-Satisfaction (0-10)	(6) Risk of Depression (0/1)
Solar Works	0.168**	0.282***	-0.020	0.061	-0.138	-0.059
	(0.083)	(0.103)	(0.066)	(0.058)	(0.244)	(0.049)
Female	-0.061	0.014	-0.019	0.005	-0.015	0.126***
	(0.049)	(0.059)	(0.040)	(0.033)	(0.141)	(0.029)
Observations	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.045	0.032	0.016	0.029	0.028	0.060
School FE	YES	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO	NO
Control Mean	2.253	1.248	1.248	2.196	5.005	18.05
Number of Schools	20	20	20	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts. Column 1 and 3 options are: 0=strongly disagree, 1=disagree, 2=agree 3=srongly agree. Column 2: 0=got a lot worse, 1=got a bit worse, 2= stayed the same, 3=improved a bit, 4=improved a lot. Column 4 0=not happy at all, 1=not very happy, 2=quite happy, 3= very happy. Column 5 scale from 0-10. Column 6 risk of depressen dummy according to CES-D scale.

Table A.14: Knowledge about Solar Lights

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Know Price	Know Charg-ing	Know Battery Run Time	Know Dura-bilit	Nr Brands Know
Solar Works	-0.056	0.519***	0.483***	0.107**	0.464***
	(0.048)	(0.048)	(0.046)	(0.049)	(0.083)
Female	0.019	-0.005	-0.069***	-0.002	-0.130***
	(0.028)	(0.028)	(0.027)	(0.028)	(0.047)
Observations	1,313	1,313	1,313	1,313	1,313
R-squared	0.070	0.080	0.163	0.070	0.120
School FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Control Mean	0.406	0.234	0.436	0.490	0.597
Number of Schools	20	20	20	20	20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Solar ownership is instrumented with price discounts.

D. Survey Questions Used for Indices

Question for Index of Symptoms of Respiratory Infections

Based on Bates et al. 2015 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 Symptoms of Dry Eyes

As for the questions about symptoms of dry eyes 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?

E. 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.

F. Pictures

Figure A.1: Tin Light

Figure A.2: Kerosene Lantern

Chapter 3

Using Sensors to Measure Technology Adoption

With Isabel Günther and Yael Borofsky

Abstract: Empirical social sciences rely heavily on surveys to measure people's well-being and behavior. Previous studies have shown that such data are prone to systematic biases caused by social desirability, recall challenges, and the Hawthorne effect, as well as random errors. Moreover, researchers can typically not collect high frequency data with surveys, which might be important for outcomes that vary over time. Innovation in sensor technology might address some of these challenges. In this study, we use sensors to describe the adoption of solar lights in Kenya and analyze the extent to which survey data are limited by systematic and random error. Sensor data reveal that households used solar lights for four hours per day on average, almost every day, and mostly in the evening and the morning. On average, self-reported use does not differ from use measured with sensors, however, random measurement errors in surveys are large. Households that used the solar light a lot were likely to underreport use, while households that used it very little were likely to overreport. Whether a household received the solar light for free, the gender of the respondent, and their wealth did not correlate with their tendency to over- or underreport. Asking about general usage provided more accurate information than asking about disaggregated use for each hour of the day. As the Hawthorne effect would predict, frequent visits from surveyors for a random subsample increased solar light use initially, but it had no long-term effects.

3.1 Introduction

Since the 1980s, improvements in research design and analytical tools have increased the scientific impact and policy relevance of applied microeconomics (Angrist & Jörn-Steffen, 2010). The increased use of natural experiments and randomized control trials (RCTs) were of particular importance to this positive development (Angrist & Jörn-Steffen, 2010; Duflo, Glennerster & Kremer, 2008). Alongside this trend, there has been an increase in the collection of household-level survey data across high-, middle-, and low-income countries. Improvements have been so important that Angrist & Jörn-Steffen (2010) talk about a "credibility revolution" in applied microeconomics. While methodological and data advances have been remarkable, much of the research still relies heavily on self-reported survey data, which are prone to measurement errors and can be expensive to collect. Recent technological breakthroughs have pushed the field to a new frontier: improving the accuracy and precision of measurements of household well-being and behavior through the use of entirely new types of data, such as satellite imagery, cortisol stress tests, cell phone network data, and information from sensors. The hope is that these novel measurement techniques can help circumvent some of the challenges associated with self-reported survey data, including social desirability bias, sampling bias, the Hawthorne effect, and recall bias.

First, respondents may be prone to social desirability bias, meaning that they tend to answer what they think the surveyor wants to hear, or what they think is socially desired (Bertrand & Mullainathan, 2001; Zwane et al., 2011; Nederhof, 1985). This bias might be particularly large when attempting to measure the adoption of a technology that is "desired" by the research team and society at large, in the sense that it has positive externalities. Examples of such socially-desired technologies include improved cookstoves (Ramanathan et al., 2016; Ruiz-Mercado, Canuz & Walker, 2013; Thomas et al., 2013; Wilson et al., 2016), water filters (Thomas et al., 2013), latrines (Garn et al. 2017; Gautam, 2017), vaccines (Banerjee et al., 2010), and bed nets (Dupas & Cohen, 2010). Second, the technology might be used by a large number of people and it may be infeasible to interview them all. Serneels, Beglee & Dillon (2016) test, for example, if information about returns to education varies depending on whether the concerned person was asked directly or another household member answered for them. Third, being surveyed (frequently) may make certain decisions more salient or remind people of certain (desirable) behaviors and thus influence respondents' behavior (Zwane et al., 2011; Smits & Günther, 2018). Simply knowing that one is being observed can also change respondents' behavior, which is referred to as the Hawthorne effect. The extent to which this effect influences social science research has been hotly debated in developed countries (Adair, Sharpe & Hyunh, 1989; Levitt & List, 2011; McCambridge, Witton, Elbourne, 2014) and emerging economies (Clasen et al., 2012; Leonard & Masatu, 2006; Simons et al., 2017). This effect is not specific to surveys, but can occur whenever participants know they are being observed. All of these problems create systematic errors and thus reduce the accuracy of any measurement. In experimental set-ups that focus on comparisons between different treatment groups, these errors are particularly problematic if they have varying effects across different treatment groups.

In addition to these well-known biases, respondents may simply not recall the answers correctly or surveyors may make mistakes in recording them (Beaman, Magruder & Robinson, 2014; Bertrand & Mullainathan, 2001; Das, Hammer & Sanchez-Paramo, 2012). Such recall errors particularly relevant for events that happened a long time ago. However, researchers still ask about events that happened (far) in the past, since in many cases, collecting high frequency data it is nearly impossible because, it is intrusive, expensive, and logistically challenging. Thus, survey data tend to be noisy for everything that fluctuates over time, even if the average across the population is accurately estimated (e.g., incidents of diarrhea). While these sources of error do not necessarily lead to systematic error, they tend to add noise to the data and reduce the precision of estimates. Hence, these random errors reduce the chances of detecting an effect of a technology or differences between sub-groups. Moreover, these types of error can still lead to systematic biases if they are more pronounced for certain sub-groups. Loken and Gelman (2017) even argue that measurement errors can increase the chances of finding spurious correlations in small sample sizes.

Recognizing these challenges, researchers have begun comparing different types of survey questions and methods, including data collected with respondent diaries. Typically, the goal of theses studies is to measure the extent of the problem and to optimize survey tools.

A number of studies discuss recall biases and optimal recall periods, for example. Das, Hammer, & Sánchez-Paramo (2012) find large differences among 1,621 individuals in Delhi in the answers to questions about weekly and monthly medical expenditures, morbidity, doctor visits, time spent sick, and whether a school or work day was lost due to illness. Beegle, Carletto & Himelein (2012), on the other hand, use variation in the time between harvests when conducting interviews in three African countries and find no evidence of large recall biases. Relatedly, studies compare recall answers with diaries, where respondents are asked to fill out information on their own at a higher frequency. De Mel, McKenzie & Woodruff (2009) find that Sri Lankan micro-enterprise owners would report higher revenues and higher expenses with diaries as compared to recall surveys, however the reported profits were similar. Along similar lines, Deaton & Grosh (2000) summarize several studies about household expenditures and find that respondents would report substantially higher food expenditure in diaries compared with recall questions.

There is a related debate about whether asking aggregated questions versus disaggregated questions leads to more accurate and precise estimates (Arthi et al., 2016; Daniels, 2001; De Mel, McKenzie & Woodruff, 2009; Grosh & Glewee, 2000; Serneels, Beglee & Dillon, 2016; Seymour, Malapit & Quisumbing, 2017). In the same study with micro-enterprise owners in Sri Lanka, the researchers find that respondents' reports of overall firm profits tended to be more accurate than when owners were asked about all the details concerning revenues and expenses. As a benchmark, they had research assistants surprise the enterprises and observe transactions (De Mel, McKenzie & Woodruff, 2009). Other studies, however, find that asking more detailed questions does lead to more accurate results. Serneels, Beglee & Dillon (2016) suggest that combining several detailed questions about labor market participation into one leads to significant biases when estimating returns to education. Seymour, Malapit & Quisumbing (2017) conclude that asking individuals about their activities for specific time intervals throughout the day (time diaries) leads to more accurate answers than asking how much time individuals spend overall on certain activities.

An important challenge for these types of studies is that they often compare different self-reported data, thus they tend to rely on benchmarks whose accuracy remains unclear.

Recently, prices for sensor technology[34] have dropped significantly and more "off-the-shelf" solutions have become available (IPA, 2016; Pillarisetti et al., 2017) allowing sensors to be used to collect data in studies with large sample sizes. This provides opportunities for researchers to use sensor data, which

[34] IPA, 2016 defines a sensor as a "device used to measure a characteristic of its environment—and then return an easily interpretable output, such as a sound or an optical signal. Sensors can be relatively simple (e.g. compasses, thermometers) or more complex (e.g. seismometers, biosensors)."

allows them to avoid some of the problems posed by survey data described above. Sensors can be used to measure the use of various technologies, such as water filters, cookstoves, or, in our case, solar lights. At this point in time, however, they do not allow researchers to measure who uses the technology.
A small, but burgeoning body of research uses sensor data to understand technology adoption in low- and middle-income countries. Some of these studies also compare sensor data to survey data and discuss different types of systemic biases, as well as random errors. In a field experiment in Guatemala, Ruiz-Mercado, Canuz & Walker (2013) used stove use monitors in 80 households to study the use of improved cookstoves. The research team additionally administered quarterly surveys, which included questions about the frequency of stove use. They find that answers from the surveys were relatively consistent with sensor data. Wilson et al. (2016) studied cookstoves in 141 households in Darfur for 4-12 weeks and find that most respondents (83%) said they used cookstoves for every meal each day, while sensor data reveal that participants only used them for half of their meals. They also find that when surveyors announced their visits, use increased amongst those who had hardly used the stove before. Similarly, Ramanathan et al. (2016) find a tendency to overreport use among 456 households in rural India (which they observed over 17-months). The research team finds little correlation between self-reported use of cookstoves and sensor data. In a field study in Rwanda, Thomas et al. (2013) compared reported usage of water filters (N=63) and cookstoves (N=70) from monthly surveys with sensor data from the same respondents. As the sensors they used were expensive (US $500 each), they deployed 50 sensors and rotated them every two weeks over the course of the five-month study. They find that respondents significantly overreport (by 17 percentage-points) the use of the improved cookstove. The overreporting for water filters was less pronounced, but still fairly large (6 percentage-points). Gandhi, Frey & Lesniewski (2016) compared survey data with sensor data from 37 solar light users over a period of less than two weeks. They find that respondents tend to overreport the use of the solar light in the survey compared to the sensor data.
To sum up, most existing studies on different technologies suggest that survey data can significantly overestimate the adoption of socially desired technologies. Two mechanisms might explain that. First, respondents may overreport if they think they are expected to use the new technology (social desiarability bias). Second, frequent interviews may change respondents' actual behavior (Wilson et al., 2016; Zwane et al., 2011). Yet, we still know little about the conditions and

types of technologies that accentuate these biases. For example, if "reciprocity" is a source of the bias – in the sense that people feel they need to be "nice" (i.e., report that they use the product a lot) because they received a free good – it could well be the case that the bias is weaker or even absent when households purchase the relevant product.

In this study, we use data from 220 sensors and a corresponding household survey to describe use patterns of solar lights. As we show in Chapter 2, switching to renewable energy sources and more energy efficient appliances can have important health and environmental benefits. However, these benefits only occur if households actually use the solar light and reduce the use of kerosene accordingly. As we saw in the case of cookstoves, even very promising technology can fail to be effective if it is simply not used (Hanna, Duflo & Greenstone, 2016). Therefore, it is crucial to get an accurate understanding of households light use patterns. In the second part of the paper, we compare sensor data with survey data, testing several hypotheses put forward in the literature about the accuracy and precision of survey data and how it can be improved. Sensor attrition was a problem, as we lost 23.2% of sensors within the first 3.5 months of the study and 37.7% before the end of the study. For this reason, we focus the analysis on measurements taken in the first month of the study, when 93.2% of the sensors still worked. Survey response attrition was 5.9% for adults and 9.1% for pupils.

In contrast to much of the previous literature, we do not find systematic overreporting of usage. In fact, the averages of survey data and sensor data look fairly similar, whereas sensor measures are even slightly higher. Households that hardly used the solar light tend to overreport use, which is consistent with social desirability bias. Households that use the solar lights frequently, on the other hand, tend to underreport use. Second, and consistent with the Hawthorne effect, we find that more frequent household visits from surveyors increased use initially, but had no effect in the long run. Third, we find that time diary questions reflect use patterns throughout the day, on average, but also that the estimates correlate very little (and less than when using aggregated questions) with sensor measures at the household level. Finally, increased precision of the sensor data allow us to see usage patterns of sub-groups more clearly, which reveal that poorer households tend to have higher solar light use.

Our findings have a number of implications for survey and sensor measurements. First, the added value of sensors seems to be particularly high where biases are expected to be large (e.g., particularly when adoption of the technology is low) or when precise estimates are needed to answer the survey questions (e.g., if the sample size is small or sub-group analysis is important). Second, for surveys, our data suggest that asking about global use estimates provides more accurate results than asking two household members about their individual use throughout the day (time diary) and combining them. Thus, while time diary questions are relevant for understanding use patterns over the course of the entire day, they do not seem to be ideal for understanding global use of a shared technology. Third, we find that frequent interactions with field staff can temporarily increase use, suggesting that researchers need to think carefully about how interactions with the field staff could bias results and, if this is a concern, aim to find ways to measure these surveyor effects. Finally, as sensor attrition was high, study designs should allow researchers to answer their main questions early on, and a first round of sensor data should be collected very soon after baseline (assuming sensor data collection does not happen remotely). Researchers using sensors should also put a protocol in place in case the testes technology used for the intervention (in our case, solar lights) or the sensor breaks before the study ends.

3.2 Study Design, Technology, and Data

The sensor data used in this paper is part of a larger RCT conducted between June 2015 and March 2016 in two sub-counties in Busia, western Kenya and described in detail in Chapter 2. The sample contained 1,410 randomly selected students (and their households) across 20 schools. In total, 400 households were assigned to the control group, 400 received a solar light for free, and 610 households randomly received an offer to buy a solar light at either 900 KES (US $9), 700 KES (US $7), or 400 KES (US $4). The randomization was conducted at the household level and stratified across schools.

Households which received free solar lights were given either a Sun King Eco or a Sun King Mobile (see Appendix, A.7 and A.8 for a picture), both manufactured by Greenlight Planet and quality assured by Lighting Global, a joint initiative of the World Bank and the International Finance Cooperation. At the time of the study, the Sun King Eco sold for US $9 in Kenya and the Sun King Mobile for US $24. According to tests conducted by Lighting Global, the Sun King Eco provides light for 5.8 hours when used at its maximum brightness of 32 lumens. The Sun King Mobile can be used for 5.4 hours in its brightest mode (98 lumens) and also charges a mobile phone (Greenlight Planet, 2016; Lighting Global, 2015). For comparison, a simple tin lamp provides around 7.8 lumens and a kerosene lantern provides 45 lumens (Mills, 2003). Both types of solar

lights provide much stronger light than the tin lights, which are most commonly used in our study context. Half of the households which received a solar light for free got a Sun King Eco and half received a Sun King Mobile. Discount vouchers were offered for the Sun King Eco model.
Of the 400 solar lights that were distributed for free to households, 164[35] were equipped with a sensor that measured usage. Households only learned about the sensors when we asked for permission to download their data for the first time, which was a few months after baseline. The research team only accessed the data if the respondent gave permission for them to do so. Of the 130[36] solar lights that were sold to households at either 900 KES (US $9) or 700 KES (US $7), a subsample of 56 solar lights was equipped with a sensor that collected data. Thus, in total, we had 220 solar lights equipped with a functioning sensor (see also next Section).

Sensor Data

We have sensor data for a total of 220 households for at least part of or the study period starting in August 2015 and ending in March 2016. By the household survey endline (February-March), around a third of sensors had stopped recording data, such that we were left with 147 sensors. The sensors stopped recording data either because the battery life ended, because the sensor was faulty (manufacturing errors), or because the solar light stopped working. It is possible that the point in time at which the sensor stopped working is correlated with usage. According to the engineering team, some sensors may have stopped working because the solar light was not used for a number of consecutive days. However, it is also likely that solar lights that are used more intensively tend to break more often. When we compare lights that broke in the previous month of usage with lights that did not, the coefficients go in different directions and we cannot conclude that one effect dominated the other (see Table A.3 in the Appendix). For these reasons, it is possible that we under- or overestimate usage when using data from the end of the study. To address possible biases, we focus most of our analysis on the first month of sensor data collection only, when 93.2% of the sensors were still working by the end of the month. An additional challenge is that 7.78% of solar lights without sensors also stopped working before the end

[35]There were an additional 28 sensors deployed that never worked. We were not able to test the all the sensors before sending them to the field due to software problems with the app.

[36]A total of 610 households received an offer to buy a lamp, out of which but only 274 did bought one. Out of these 130 were sold at either 900 KES (US $9) or 700 KES (US $7), the remaining 144 were sold at 400 KES (US $4).

of the study. Sensors increased the chances of a light breaking to 20.53%, but we cannot tell from the data whether the solar light broke, the sensor broke, or both. We can thus only provide information about working solar lights and replaced data points with missing values once the sensor stopped logging data. In this sense, all results should be interpreted as "usage conditional on the lights functioning."

For the sensor data we report the following measures of average daily use of solar lights:

- Entire Study (all): recorded use by sensors, no matter how long they worked (N = 220). Data were used from all the days that we have data for. Once a sensor stopped working the remaining days were coded as missing. Months included: August 2015-March 2016.
- Entire Study (worked entire study): sensors that worked until the end of the study, data were used from all the days we have data for (N = 147). Months included: August 2015-March 2016.
- First Month (all): sensors, no matter how long they worked (N = 220). Data were used from the first month of the study. Once a sensor stopped working the remaining days were coded as missing. Months included: August 2015.
- First Month (worked entire month): sensors that worked until the end of the first month of the study (N = 205). Data were used from the first month of the study. Months included: August 2015.
- Previous Day: sensors that worked until the end of the study (N = 147). Data were used from the day before endline data collection. Days include: Varying days in February and March 2016, depending on the day the endline was conducted in each household.

Sensors tracked when the solar lights were turned on and off. Based on this information, we calculated the total number of minutes a solar light was used on any given day of the study. Independent of the measure used, we first calculated average use by sensor, meaning that we always weight each sensor equally, regardless of the number of days of data we have.

A random subsample of those with a solar light sensor (37.1%) were subject to around five additional household visits, since they also had additional sensors installed to measure kerosene use. Other studies have found that more frequent interactions between households and surveyors led to increased use, so we also use this variation to see whether additional household visits lead to more solar light use in our study (Wilson et al., 2016; Zwane et al., 2011).

Sensor Technology

We used Bluetooth-enabled Solar Lamp Usage Monitors (referred to as sensors or solar sensors throughout this paper) to determine when the lamp was in use by measuring the change in voltage of the solar lamp's light emitting diode (LED). This sensor was installed by soldering the sensor to the board inside the light (Appendix, Figure A.5). Using smartphones enabled with Bluetooth and an iPhone App ("Lamplogger") developed specifically for these sensors, field officers visited households and wirelessly uploaded data directly from the sensor to the phone (Appendix, Figure A.6).

These sensors, along with the iPhone application, were specifically developed for this study. Since the use of sensors in field experiments is still relatively new and other researchers may find themselves in a similar situation to ours, we will share a few key lessons learned about implementing and managing sensor technology in the field.

First, it is critical to thoroughly pre-test sensor technology (both the sensor and the application to access the data, in our example) at a reasonably large scale in the field and to only roll out the study once all problems are solved. It might make sense to agree in advance on a threshold of acceptable failure rates in the pilot as a commitment device. For example, in our case, the application designed to access the data from the sensors initially did not work reliably and we were overly confident about our ability to solve the problem quickly. It took a substantial amount of troubleshooting to determine the source of the problem. In the meantime, we had to send our field officers back to the same households multiple times to ensure the data were collected, and since some of the sensors stopped working before the application was fully functioning, we ended up losing a significant amount of valuable data. Additionally, because we installed the sensors in a pre-existing product that was not designed to hold a sensor, several sensors probably stopped working due to an imperfectly soldered connection between the sensor and the existing hardware, which also led to more light breakages. Such issues could possibly be avoided by working with an expert in sensor technology to conduct extensive pre-testing of all aspects of the sensor technology package in the field (or by using a sensor technology that has already been extensively field tested).

Second, if the sensor is not constantly transmitting data throughout the study, we recommend doing a first round of sensor data collection immediately after installation and distribution (i.e., immediately after baseline). Similarly, attrition of sensors over time turned out to be a major problem in our study. Collecting data early not only ensures some data is collected from the maximum number of sensors, but can also help identify problems before they become widespread.

As a result of the two issues mentioned above, our third recommendation is to create a very detailed protocol on how to proceed if a sensor or the host technology stops working, and ideally to include it in the pre-analysis plan. Both sensors and solar lights stopped working more often than we expected, and it was not possible to distinguish from the sensor data if the solar light broke because of the sensor or vice versa. It is therefore important to have clear instructions about what to do if a solar light (or sensor) fails and to keep detailed information about replacements in order to easily account for these sensors in the analysis.

Fourth, researchers might underestimate the trade-offs between sample size and study duration on the one hand and data collection cost and management capacity on the other hand. While the data collection itself is very cheap, managing sensors and solving problems that affect many households over a long period of time is not. Researchers who plan to use sensors at a large scale should plan to allocate considerable management and field staff time to manage them. In cases where the sensor technology has not been tested extensively in the field, and over long periods of time, we also recommend designing the research in such a way that most important questions can be answered even if there is a lot of sensor attrition over time.

Our final recommendation is to take time to explain the sensor technology to partner organizations and the community. For example, we co-wrote a letter with the engineering team that developed the sensors explaining the functionality of the sensors to our partner organization. We also tested the acceptability of the sensors with a separate sample and developed a detailed script to explain the sensors to users. This script was written with guidance from our local partners, who are very familiar with the resident community. In addition, we provided respondents with our contact information in case of problems. We had no problems with regard to the acceptability of the sensors in the local community, but we imagine that this is highly context dependent. We also caution researchers to avoid "falling in love" with the sensor technology. When problems with the sensors or the application arose, we were often quick to assume that we or the field team had made a mistake instead of checking to see if the technology was malfunctioning. Both human error and technological failure are possible and, in the rush to solve problems quickly, it is important to build up a testing protocol to help you troubleshoot efficiently.

Survey Data

The endline household survey was conducted in February and March 2016 and contained, among others, questions about household light use habits (the full survey is available from the authors upon request). Information about solar light use came from two separate questions:

- Aggregated Question: one question asked the adult respondent for an estimate of total light used by the household on the previous day (N = 161).
- Detailed Question: a separate battery of questions asked each individual about their activities[37] and light[38] use for specific 30-minute time-slots between 7:00 pm and 7:00 am, corresponding to nighttime (dark) hours in Kenya. We faced a trade-off between level of detail and survey length. Ultimately, we only asked for this level of detail about light usage at night in order to limit both financial costs and the personal "cost" to the respondent in terms of patience and attentiveness (N = 215 for adults, N = 205 for children).

[37]Options: at work (non-agricultural work), barber/salon bathe, dress brewing alcohol care for children / sick / elderly clean, dust, sweep, wash dishes or clothes, ironing, other household chores cook, prepare food discuss activities of the next day with partner doctor/hospital visit eat farm work fetch water, firewood fishing or hunting Funeral/wedding activities help homework herding animals/ work with livestock listen to radio other religious activity (e.g. study, group) participate in community activities / meetings / voluntary work play sports pray prepare children for school read book repairs around / on home rest sewing/fixing clothes shop for family sleep socialize with other household members socialize with people outside of the household spend time with spouse / partner study / attend class travel by bicycle travel by foot travel by motorized means visit / entertain friends watch TV Other

[38]Options: Electricity powered lighting Solar home system powered lighting Tin Lamp Kerosene lantern/Hurricane Fire Wood Battery powered torch/lantern Candle Solar lantern/solar torch Pressurized Kerosene Lantern Other rechargeable lantern Cell phone light No lighting used Matchsticks Other.

We asked both adults and pupils the Detailed Questions and used both of these measures separately and combined (see Section C for details on this section). To calculate these measures, we created a dummy indicating whether the adult/child used the solar light during each slot. For the combined measure we created a separate dummy equal to one if either the child or the adult used the solar light and zero otherwise.

It is important to note that a respondent was only asked the Aggregated Question if they indicated that "any of their solar lights still work," due to a skip pattern in our survey instrument. A total of 53 households reported instead that their solar light did not work. Of these 53 households, 21 (40%) still had a working solar light and had, according to the sensor data, used it the previous day, suggesting that either they did not understand the question, did not know that their light still worked, or intentionally deceived the surveyors.[39] Thus, we only have an answer to the Aggregated Question from 161 respondents, from whom we also have sensor data.

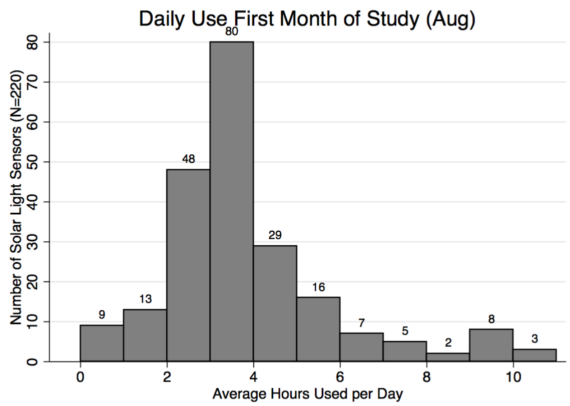
3.3 Use of Solar Lights

As discussed in Section 3.2, we focus on results from the first month of the study (August 2015) for the analysis of solar light use, since 93% of the sensors worked through August, whereas by March 2016 an additional 13.6 sensors had dropped out each month (on average). That said, results for the entire study period are very similar to results from the month of August. For each table and graph presented in this section we refer to the corresponding table and graph reporting the result for the entire study period in the Appendix. Households used the solar light on average 6.4 out of seven weekdays and 58.6% of households used the solar light on every single day of the study. During the first month of the study, households used the solar light for 3.86 hours per day and most households used the solar lights between two and five hours per day (see Figure 3.1 and Table 3.1, Row 3). Daily use across the entire study period is actually slightly higher (4.07 hours per day), possibly since schools were still closed during the first two months of the study (Table 3.1, Row 1). There are only nine households (4% of all households with sensors) who used the solar light for less than one hour per

[39] According to sensor data, households which indicated that at least one of their solar lights worked during endline did not use their solar lights for different amounts of time per day on average compared with households that said that none of their lights worked (that is for the days that the sensors still logged data).

day on average (Figure 1). The corresponding distribution for the entire study period can be found in Figure A.2 in the Appendix.
These findings of high rates of solar light usage across all households contrast with recent findings about improved cookstoves. Willson et al. (2016), for example, find that 29% of households hardly used the technology.[40]

Figure 3.1: Average Hours Solar Lights are Used per Day



Notes: This graph shows sensor data about the average number of hours the solar lights were used per day during the first month of the study.

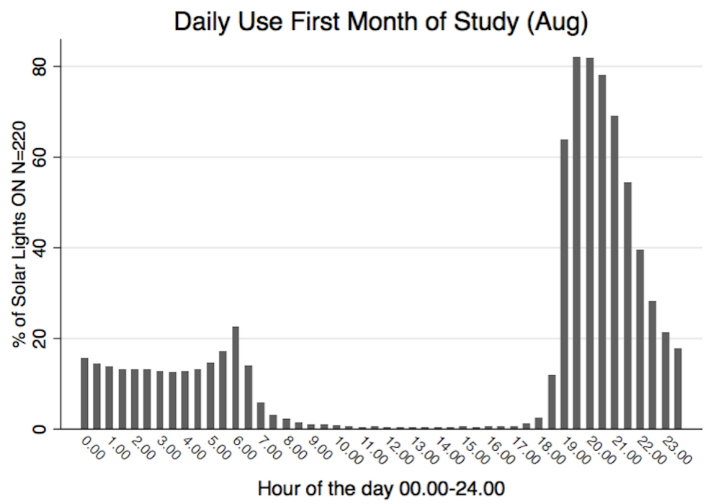
Sensors also provide detailed information on how usage of a technology varies throughout the day, throughout the week, and throughout the month. In addition, it allows researches to collect data over a long period of time. Such information is usually very time consuming, expensive, and/or intrusive to collect with surveys, especially if a technological device is used by several people, who all need to be asked about the timing of their usage individually (and repeatedly). For example, in our case, the adults we interviewed simply might not know whether their children used the solar light at night. One would have to separately ask all household members to get the full picture. It is also hard to get information about use over a long period of time with survey data because conducting many survey rounds is costly and asking respondents about time periods that lie far in the past might lead to noisy and perhaps even biased results (recall bias). Sensors, on the other hand, record the time when the solar light was used by any household member, but, unfortunately, we cannot learn

[40]The defied “non-users”, as using the cookstove less than once on 10% of days.

from the sensor data who in the household used the solar light.
Figure 3.2 shows the share of solar lights that were used, reported in half-hour slots, averaged over all days of the first month of the study. We created a dummy for every half-hour slot, which is equal to one if the solar light was used for more than 15 minutes in a row during that half hour and zero otherwise. We then calculated for each sensor the percentage of days that the light was on a (as a percentage of all days that the sensor worked) and used this information to calculate the average across all sensors. We find that households mostly use the solar light during evening hours. The half-hour interval when most solar lights (81.94%) were switched on was between 7:30 pm and 8:00 pm, which is right after sunset in Kenya. As expected, there is also a peak, albeit a smaller one, during morning hours, in particular between 6:00 am and 6:30 am. Interestingly, between 15-20% of households also have the solar lights switched on during nighttime hours. Anecdotal evidence suggests that, among other reasons, some use the solar light as a security light during the whole night or when they get up to use the restroom or check on their cattle. As expected, use is lowest during the day — 1.05% used them at most during daytime (between 9:00 am and 5:00 pm) (Figure 3.2).

Sensors can also be used to study changes in use over time. Households might increase use of the product as they learn about its advantages or develop a habit of using it. Households might decrease use if they discover unexpected disadvantages or if their excitement over the novelty of the product wears off over time. Use could also vary with the schooling or agricultural schedule. Figure 3.3 shows use over the eight months of the study period for the 147 solar lights for which we have data until the end of the study. Use was slightly lower in August and September, but none of the differences are statistically significant (Appendix, Table A.1). This pattern could be linked to the fact that schools were closed in August, due to holidays, and in September, due to a teacher strike. However, as explained in Section 3.2, around a third of the sensors did not survive until the end of eight-month study and we do not know how use would have evolved amongst those households whose lights/sensors did not survive.
The second figure breaks down usage by day of the week (Figure 3.3). We observe that solar lights are used less on the weekend. This difference is statistically significant at the 5% level (Appendix, Table A.2). On average, households switched the light on and off 4.74 times per day (SD 3.35) with each on/off

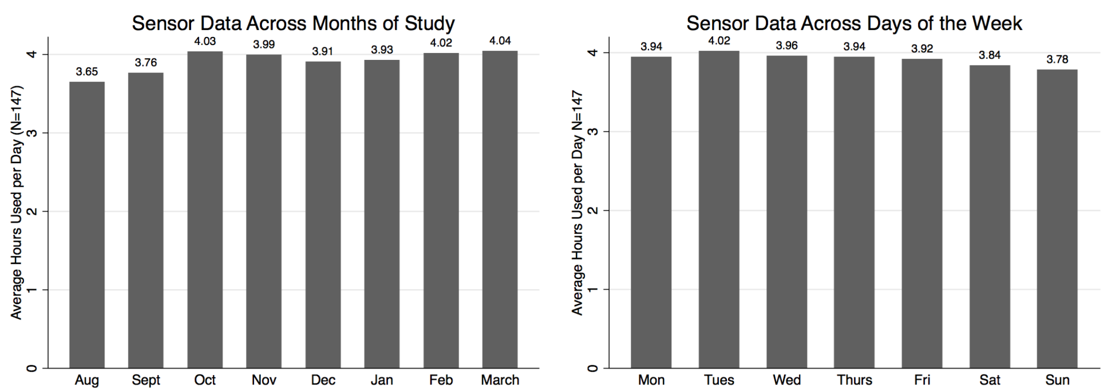
Figure 3.2: Use Across the Day



Notes: We classify usage by whether the solar light was used for more than 15 minutes without interruption during the relevant half-hour slot. We then calculated for each sensor the percentage of days that the light was on across all days that the sensor worked and then used this information to calculate the average across all sensors. Sample is restricted to sensors that worked until the end of the study.

event lasting an average of for 50.71 minutes (SD 93.32); 50% of all use events were shorter than 12 minutes.

Figure 3.3: Daily Use Across Months of the Study and across Days of the Week



Notes: Sample is restricted to sensors that worked until the end of the study.

3.4 Comparing Survey and Sensor Data

In this section we analyze whether estimates of technology use measured with survey data are similar to estimates of technology use measured by sensors. Moreover, we test several hypotheses that have been discussed in the literature about what drives the accuracy of survey data. Lastly, we analyze whether sensor data which measure technology use with higher precision allow us to detect differences across sub-groups or experimental treatments with smaller sample sizes.

Table 3.1: Mean Light Use (Hrs) per Day: Survey and Sensor Data

	(1) All Data Mean (SD)	(2) All Data Obs	(3) Exclude Missing Means (SD)	(4) Exclude Missing Obs
(1) Sens (All)	4.067	220	3.813	125
	(1.776)		(1.464)	
(2) Sens (All)- Worked until End	3.731	147	3.813	125
	(1.404)		(1.464)	
(3) Sens (Aug)	3.864	220	3.607	125
	(2.031)		(1.846)	
(4) Sens (Yest.)	3.706	147	3.777	125
	(2.132)		(2.247)	
(5) Surv (Detail)	3.388	215	3.616	125
	(1.764)		(1.625)	
(6) Surv (Detail)- Adult	3.193	215	3.152	125
	(1.377)		(1.371)	
(7) Surv (Aggr.)	3.573	161	3.492	125
	(2.073)		(2.030)	

Notes: Column 1 and 2 include all data, Column 3 and 4 only the 125 observations where we have all sensor and survey variables listed in this table (see Section 3.2 for further explanations). Row 1 includes all sensors no matter when they stopped working, Row 2 includes only sensors that worked until the end of the study, Row 3 includes data from all sensors for the month of August only, Row 4 includes sensor data for the day before the study, Row 5 shows survey data from the Detailed (hour by hour) Questions for adults and pupils combined, Row 6 shows the same question as Row 5, but only for adults, and Row 7 shows the Aggregated Questions where we asked about use of the entire household (see questions in Appendix, Section C.)

Table 3.2: Differences in Light Use (Hrs) per Day: Survey and Sensor Data

	(1) Sens (All) All	(2) Sens (All) Worked until End	(3) Sens (Aug) All	(4) Sens (Yest.)	(5) Surv (Detail)	(6) Surv (Detail) Adult	(7) Surv (Aggr.)
(1) Sens (All)	0.000	0.000	0.203 ***	0.025	0.654 ***	0.849 ***	0.513 ***
	(220)	(147)	(220)	(147)	(215)	(215)	(161)
(2) Sens (All)	-	0.000	0.229 ***	0.025	0.074	0.557 ***	0.321 *
Worked until End		(147)	(147)	(147)	(147)	(147)	(125)
(3) Sens (Aug)	-	-	0.000	-0.204	0.450 **	0.645 ***	0.288
			(220)	(147)	(215)	(215)	(161)
(4) Sens (Yest.)	-	-	-	0.000	0.049	0.532 ***	0.285
				(147)	(147)	(147)	(125)
(5) Surv (Detail)	-	-	-	-	0.000	0.195	0.085
					(215)	(215)	(161)
(6) Surv (Detail)	-	-	-	-	-	0.000	-0.430 **
Adult						(215)	(161)
(7) Surv (Aggr.)	-	-	-	-	-	-	0.000
							(161)

Notes: This table shows differences between variables in Rows and Columns. *** p<0.01, ** p<0.05, * p<0.1. Number of observations are shown in brackets. Number of observations varies since we do not have sensor data for all sensors until the end of the study and we do not have all survey measures for all observations.

3.4.1 Averages from Sensor and Survey Data are Similar

Comparing the different survey answers with the sensor data, we find that the averages from sensor data and from survey data are relatively similar for most measurements (Table 3.1). When we asked respondents to estimate the overall use of the solar light, on average, their estimates were statistically not different from one another, with the exception of one (Table 3.2, Column 7, Rows 1-4). This self-reported estimate is only different from the first sensor measure (i.e., across all sensors and the entire study period, Table 3.2, Row 1) and the self-reported measure is smaller than the measure from the sensors. As expected, the Detailed Questions (Table 3.1, Row 5), which asked one adult and one child in each household about their personal use, elicit responses that are on average lower than the Aggregated Question as it does not include information from all household members. The estimate in Row 6 (Table 3.1) reflects adults' responses to the Detailed Questions and is thus lower than the combined measure in Row 5 (Table 3.1).

These findings stand in contrast to most of the recent literature (Thomas et al., 2013 or Wilson et al., 2016, for example) studying the use of improved cookstoves with sensor and survey data, which find that respondents tend to overreport use on average. There is, however, an important difference between our study and previous work, namely that, in our case, adoption of solar lights was nearly universal, while adoption of improved cookstoves was typically low (see Section 3.3 for further discussion). We also find that households which hardly use the solar lights tend to overreport use, while households that use the solar light a lot tend to underreport use (Appendix, Table A.5). In our case, however, there are very few households that hardly use the solar lights and hence, we do not find overreporting on average. This will be further discussed in the next section.

3.4.2 Frequent Users Underreport - Infrequent Users Overreport

We analyze whether certain sub-groups are more likely to under- or overreport usage. First, we test whether households which received a free solar light are more likely to overreport use of solar lights than those who paid for it. If there is a reciprocity dynamic at play, in that recipients of free lights feel more obliged to say positive things about the gift they received, then one would expect that households receiving a free light would be more likely to overreport use. Our data do not confirm this hypothesis (Table 3.3, Column 2). There is also no evidence that the gender of the respondent influence the extent to which their answers differed from the sensor measurement (Table 3.3, Column 3).

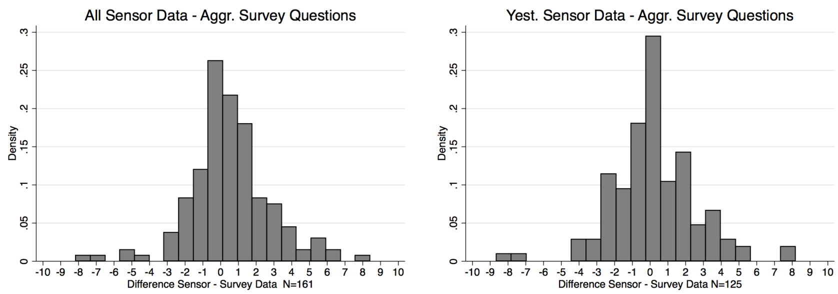
Table 3.3: Analysis of Under- and Overreporting Solar Light Use

VARIABLES	(1) Diff Sens-Surv (All data)	(2) Diff Sens-Surv (All data)	(3) Diff Sens-Surv (All data)	(4) Diff Sens-Surv (All data)	(5) Diff Sens-Surv (All data)	(6) Diff Sens-Surv (All data)	(7) Diff Sens-Surv (All data)
Hours Used (Sensor)	0.683***	0.682***	0.687***	0.671***	0.673***	0.677***	0.688***
	(0.123)	(0.123)	(0.123)	(0.123)	(0.168)	(0.131)	(0.124)
Free Solar Light		0.261					
		(0.347)					
Respondent Female			-0.305				
			(0.339)				
Additional Visits				0.384			
				(0.320)			
Wealth Index					-0.075		
					(0.120)		
HH Head Yrs of Schooling						0.038	
						(0.046)	
HH Size							-0.045
							(0.058)
Constant	-2.279***	-2.470***	-2.104***	-2.371***	-1.809*	-2.494***	-2.003***
	(0.449)	(0.542)	(0.515)	(0.447)	(0.980)	(0.540)	(0.543)
Observations	161	161	161	161	120	152	161
R-squared	0.247	0.250	0.251	0.254	0.227	0.236	0.249
Mean	0.513	0.513	0.513	0.513	0.513	0.513	0.513

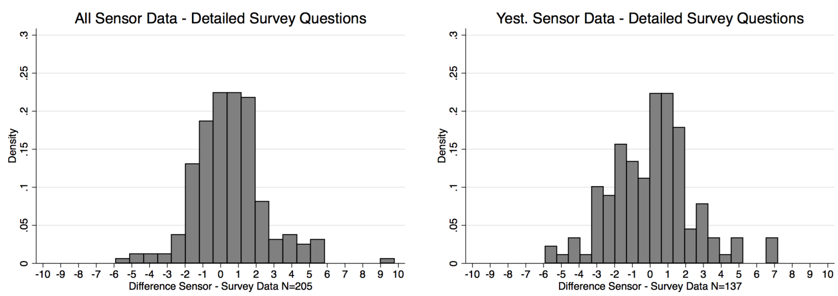
Notes: Robust standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Includes all 161 sensors for which we have the aggregated survey measure. Column 5 has fewer observations since we only collected data on assets for a subgroup.

In our setup a random sub-sample received more frequent visits and monitoring. Table 3.3 shows that these additional visits did not make households more likely to overreport use which is probably reassuring for researchers worried that frequent interactions with surveyors might alter responses (Zwane et al. 2011). We also test for a change in behavior (higher usage) among those houeholds in Section 3.4.3. Households' wealth and size, as well as the household head's level of education, do not correlate with reporting differences (Table 3.3, Column 5-7). We do find, however, that underreporting strongly correlates with use. Thus, the more a household uses a solar light, the more likely they are to underreport use. The opposite also holds, whereby infrequent users are more likely to overreport (Table 3.3 and Appendix, Table A.5, Figure A.4). There could be a couple of explanations for this observation: first, respondents could have a certain reference point in mind regarding reasonable light use that they report regardless of actual light use. It is also possible that underreporting occurs because respondents are not aware of other household members' use (in particular in high-usage households), while respondents who hardly use the solar light overreport because they feel they are expected to use the light (social desirability bias).

Figure 3.4: Under- and Overreporting of Use



Notes: Graphs show density of difference between sensor data (where we include data from all sensors over the entire study period on the left, and only from the day before endline on the right) and survey data, where we asked the adult for a global estimate of the solar light use on the previous day (Exact Question can be found in Appendix, Section C).



Notes: Graphs show density of difference between sensor data (where we include data from all sensors over the entire study period on the left, and only from the day before endline on the right) and survey data, where we asked the adults and pupils hour by hour about their activities and light use (time diary questions) and added the hours that either the adult or the pupil indicated that they used the solar light up (Exact Question can be found in Appendix, Section C).

3.4.3 Intense Monitoring Temporarily Increased Use

As previously explained, 37% of randomly selected households with solar lights and sensors were exposed to more frequent visits by surveyors at the beginning of the study. This treatment difference allows us to measure whether these households tend to use the solar lights more, perhaps because they feel more observed. More frequent visits did indeed increase use in the first month of the study; however, this difference disappeared thereafter (Table 3.4). Different mechanisms might explain this difference: respondents might have felt more observed and used the novel product more as a result (Clasen et al. 2012; Leonard & Masatu 2006; Simons et al., 2017), the visits may have made the product more salient (i.e., reminded respondents of the product) (Zwane et al., 2011; Smits & Günther, 2018), or the surveyors might have accelerated learning about the product.

Table 3.4: Hawthorne Effect

VARIABLES	(1) Sensor (Hrs) First Month	(2) Sensor (Hrs) First Month	(3) Sensor (Hrs) All Months	(4) Sensor (Hrs) All Months
Frequent Visits	0.584**	0.589**	0.339	0.278
	(0.284)	(0.296)	(0.253)	(0.239)
Observations	220	147	220	147
R-squared	0.019	0.026	0.009	0.009
Mean	3.646	3.285	3.941	3.629

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column 1 and 3 include all sensor data, while Column 2 and 4 are restricted to those that worked until the end of the study.

3.4.4 Time Diary Questions vs. Aggregated Questions

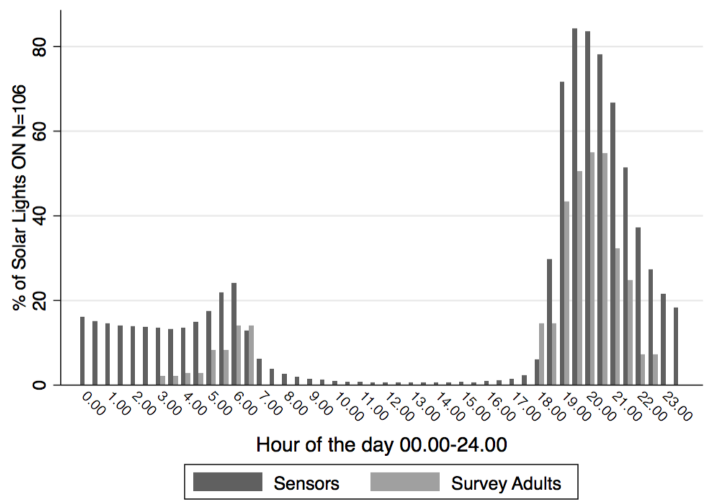
In the survey, we asked about solar light use in two different ways. First, we asked adults and children to report the activities they engaged in for each one-hour slot in the morning and half-hour slot in the evening (see Section 3.2 for more details) and then, whether they used any lighting source for each activity in each time slot. Second, we asked adults to estimate the global use of the entire household on the previous day (Aggregated Question) (see Section 3.2 for more details).

Using sensor data, we calculated the percentage of days that the light was used during that specific time slot for each sensor (across all days that the sensor worked), and then used this information to calculate the average across all sensors. By "used" we mean that the solar light was used for more than 15 minutes without interruption during the relevant half-hour slot.

In Figure 3.5 and 3.6, we compare the Detailed Survey Questions with the sensor measures. Overall, we see that the patterns of solar light usage over the course of the day match well. Note that we did not ask about use during the day and late at night, and hence these slots are, by design, not filled. As expected, adults' reported use only reflects a fraction of total use. This is consistent with adults' answers to a separate question, to which over 70% responded that their school-aged children were the main users of the solar light (see Chapter 4). Figure 3.6 compares the combined answers of adults and pupils with sensor data. While the reports of usage in the evening hours seem to match the sensor data very well, some children seem to overreport use in the early morning hours.

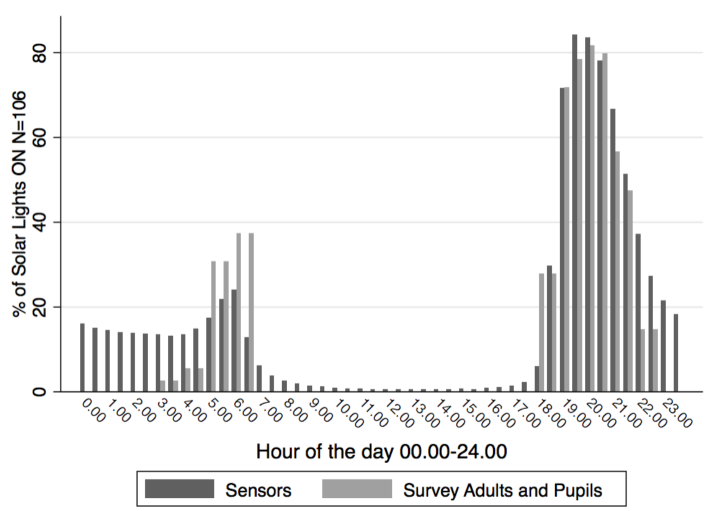
Comparing the averages of the Aggregated Question and the Detailed (or time diary) Questions, we observe that both measures provide similar results, which are both statistically indistinguishable from the sensor data for usage the day before the survey was done (Table 3.2, Column 5 and 7). The correlation coefficients in Table 3.5 (Column 5 and 7) suggest, however, that the Detailed Questions are less correlated with use than the Aggregated Question. In fact, their correlation coefficients are all below 0.1. This result might be surprising, given that the consensus in the time-use literature is that asking individuals about each time slot separately (time diaries) is considered best practice to measure time use (Seymour, Malapit & Quisumbing, 2017). This finding might be explained by the fact that we did not ask for use during the entire 24 hours in the Detailed Questions, and that we only asked two household members and thus do not capture usage by the entire household. Nevertheless, it is interesting that this much more lengthy and costly survey method did not correlate more with sensor data than simply asking for a global average.

Figure 3.5: Use Across the Day: Sensor vs. Survey Data (Adults Only)



Notes: For the sensor data, we classify usage by whether the solar light was used for more than 15 minutes without interruption during the relevant half-hour slot. We then calculated for each sensor the percentage of days that the light was on across all days that the sensor worked and then used this information to calculate the average across all sensors. In the survey we asked about activities and light use for each time-slot separately. Sample is restricted to sensors that worked until the end of the study and households where we have endline data for adults and pupils.

Figure 3.6: Use Across the Day: Sensor vs. Survey Data (Adults and Pupils)



Notes: For the sensor data, we classify usage by whether the solar light was used for more than 15 minutes without interruption during the relevant half-hour slot. We then calculated for each sensor the percentage of days that the light was on across all days that the sensor worked and then used this information to calculate the average across all sensors. In the survey we asked about activities and light use for each time-slot separately (in this graph we count the light as being used if either the pupil or the adult indicated that they used it). Sample is restricted to sensors that worked until the end of the study and households where we have endline data for adults and pupils.

3.4.5 Precision Gains with Sensor Data

While self-reported daily use of solar lights looks very similar to survey data on average (Table 1 and 2), the individual observations are not highly correlated (Table 3.5). In particular, correlation coefficients of the Detailed Questions (Table 3.3, Column 5 and 6) are very small, suggesting that the data are very noisy. This makes it hard to detect small differences with survey data.

Table 3.5: Correlations Light Used (Hrs) per Day: Survey and Sensor Data

	(1) Sens (All) All	(2) Sens (All) Worked until End	(3) Sens (Aug) All	(4) Sens (Yest.)	(5) Surv (Detail)	(6) Surv (Detail) Adult	(7) Surv (Aggr.)
(1) Sens (All)	1.000	1.000	0.883	0.505	0.062	-0.035	0.257
	(220)	(147)	(220)	(147)	(215)	(215)	(161)
(2) Sens (All)	-	1.000	0.809	0.505	0.150	0.100	0.303
Worked until End		(147)	(147)	(147)	(147)	(147)	(125)
(3) Sens (Aug)	-	-	1.000	0.314	0.064	0.027	0.338
			(220)	(147)	(215)	(215)	(161)
(4) Sens (Yest.)	-	-	-	1.000	0.065	0.127	0.372
				(147)	(147)	(147)	(125)
(5) Surv (Detail)	-	-	-	-	1.000	0.334	0.409
					(215)	(215)	(161)
(6) Surv (Detail)	-	-	-	-	-	1.000	0.317
Adult						(215)	(161)
(7) Surv (Aggr.)	-	-	-	-	-	-	1.000
							(161)

Notes: Table shows correlations between variables in Rows and Columns. Number of observations are shown in brackets. Number of observations varies since we do not have sensor data for all sensors until the end of the study and we do not have all survey measures for all observations.

An advantage of sensor data is that it allows for more precise measurements, which enables researchers to detect smaller differences in use among sub-groups or to use smaller sample sizes than are necessary when conducting surveys. For example, in our study we were interested in knowing whether households that received a free light used it less than households that paid for the light. This is important to understand since we are interested in the potential effectiveness of subsidies in increasing adoption. One might expect that households which purchase a solar light use it more, as households expecting to use the light a lot are more likely to buy one (selection effect); simply having already paid for the solar light may also make them more likely to use it (sunk cost effect). Moreover, we were interested in whether poorer households use solar lights more. Unlike purchasing kerosene for kerosene lighting, the marginal cost of an additional hour of solar light is effectively zero. Therefore, we would expect more credit-constrained households to shift their light consumption away from kerosene and towards the solar light once they obtain access. In Table 3.6, we show how the use of solar lights varies for different sub-groups. We show survey answers for the households with sensors to get a sense of the gains in precision from sensor data within the same sample, as well as survey answers from the entire sample. Comparing household solar light usage for different types of households, we find that neither the survey nor the sensor data indicate a statistically significant difference in usage between those households which received a solar light for free and those who paid for it (Table 3.6, Columns 1-3). Our finding is in line with research on other products, such as bed nets, where the authors also did not find differences in net usage between households that paid for the nets and those that received them for free (Dupas & Cohen, 2010). Interestingly, a number of variables suggest that poorer households use the solar light more. Survey data and sensor data indicate that households with lower quality floors use the solar lights more (Table 3.6, Columns 4-6). This effect is more significant and the point estimates are larger when using sensor data. The difference can only be detected with survey data if we use the entire dataset (Table 3.6, Column 6) and not only those households which also had a sensor (Table 3.6, Column 5). In line with this finding, food-insecure households also tend to use the solar light more (Table 3.6, Columns 7-9). In this case, both the size of the coefficient and the standard errors from the survey responses (Table 3.6, Columns 9) from the entire dataset and the sensor data (Table 3.6, Columns 7) are very similar. If we restrict the survey data, the point estimate is larger (Table 3.6, Column 8). There is also a negative correlation between asset ownership and solar light use, albeit it is only (marginally) significant (Table 3.6, Column 10) and not correlated with survey answers (Table 3.6, Columns 11 and 12). As we show in Chapter 2, households tend to use the solar light as a substitute for kerosene, but still use both lighting sources. These results seem to confirm that more credit constrained households tend to use the solar lights more. This is consistent with a story where poorer households are more prone to shift their light consumption away from kerosene towards the solar light once they get access.

Table 3.6: Correlates of Light Use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Sensor (Hrs) First Month	Survey (Hrs) with Sensors	Survey (Hrs) All	Sensor (Hrs) First Month	Survey (Hrs) with Sensors	Survey (Hrs) All	Sensor (Hrs) First Month	Survey (Hrs) with Sensors	Survey (Hrs) All	Sensor (Hrs) First Months	Survey (Hrs) with Sensors	Survey (Hrs) All
Free Light	0.203	-0.246	-0.120									
	(0.348)	(0.362)	(0.175)									
Earth Floor				1.065***	0.364	0.354*						
				(0.325)	(0.462)	(0.202)						
Freq Cut Meal							0.246*	0.390**	0.243***			
							(0.136)	(0.162)	(0.087)			
Wealth Index										-0.177*	0.024	0.153
										(0.100)	(0.114)	(0.099)
Constant	3.712***	3.756***	3.505***	2.946***	3.261***	3.133***	3.685***	3.297***	3.250***	4.764***	3.394***	2.647***
	(0.314)	(0.306)	(0.134)	(0.288)	(0.426)	(0.178)	(0.160)	(0.185)	(0.102)	(0.508)	(0.545)	(0.466)
Observations	220	161	495	215	161	495	215	161	495	164	120	293
R-squared	0.002	0.003	0.001	0.038	0.004	0.004	0.016	0.041	0.020	0.019	0.000	0.018
Mean	3.864	3.566	3.434	3.864	3.566	3.434	3.864	3.566	3.434	3.864	3.566	3.434

3.5 Conclusion

There are a number of challenges with self-reported data on technology adoption, including social desirability bias, biases related to the fact that respondents feel observed, and accurate information recall. Sensors can provide more accurate data at a higher frequency than self-reported data. In addition, they can help us understand biases and improve survey design, as we can test different survey techniques and compare responses to data collected with sensors. Sensor technology has the potential to transform how we measure human behavior and track the performance of policies and programs, however, there are still challenges to be overcome regarding the functionality of the technology over time. More field testing and training for researchers as well as field staff and managers in charge of dealing with these new tools is needed (see Section 3.2 for more details).

While a number of studies use sensors to measure the adoption of cookstoves (Wilson et al., 2016; Ramanathan et al., 2016; Thomas et al., 2013), this study is the first to use sensors to measure the adoption of solar lights on a large scale. Gandhi, Frey & Lesniewski (2016) used sensors to measure solar light adoption in 37 households over less than two weeks. We were able to use sensors to collect information about solar light use in over 200 households, some of which purchased the solar light, while others received one for free. We find that households use solar lights for around four hours per day on average and that fewer than 5% of households hardly use the solar lights. Adoption of solar lights is much higher than what recent studies on cookstove adoption have found (Wilson et al., 2016). We also used sensor data to test what types of survey questions led to more accurate answers and whether differences between self-reported information and sensor data were particularly large for certain sub-groups.

A number of results seemed especially relevant: first, as opposed to a number of papers on cookstoves (Wilson et al., 2016; Ramanathan et al., 2016; Thomas et al., 2013), and the small-scale study on solar lights (Gandhi, Frey & Lesniewski, 2016), we do not find that households systematically overreport use of solar lights. However, in line with the findings of these studies, overreporting was more likely when the household used the solar light very little, which could be explained by social desirability bias. In addition, we also find that households which use the solar light a lot tend to underreport use, which, to our knowledge, has not been found before. As adoption of solar lights was nearly universal, we do not find evidence for systematic overreporting on average. In addition to the difference in adoption rates between cookstoves and solar lights, the nature of solar light usage is also very different from cookstove usage. Solar lights can be used by many household members throughout the entire day and in ways that are not visible to the respondent, whereas the use of cookstoves is typically reserved for a few household members and for a limited number of times at fixed times of day. These differences might explain why underreporting was more common in our case.

Second, while the reported hours of use per day are quite similar on average, answers from individual households correlated very little with the information we got from the sensors, suggesting that random errors are very large.

Third, we find that asking aggregated questions about use provides more accurate information than asking for each time slot separately (time diary). This result is surprising, given that time diaries are considered the gold standard in time-use data collection. However, there are still very few papers confirming the validity of this claim in developing countries (Seymour, Malapit & Quisumbing, 2017). The lack of correlation between the time diary survey responses and the sensor data could also be due to survey design issues, as we did not ask for every time-slot throughout the day and we did not survey every household member.

Finally, we find that, as predicted by the Hawthorne effect, more frequent visits from surveyors in the beginning of the study did increase use initially. This difference disappeared once the visits stopped. Wilson et al. (2016) made a similar discovery when studying cookstoves.

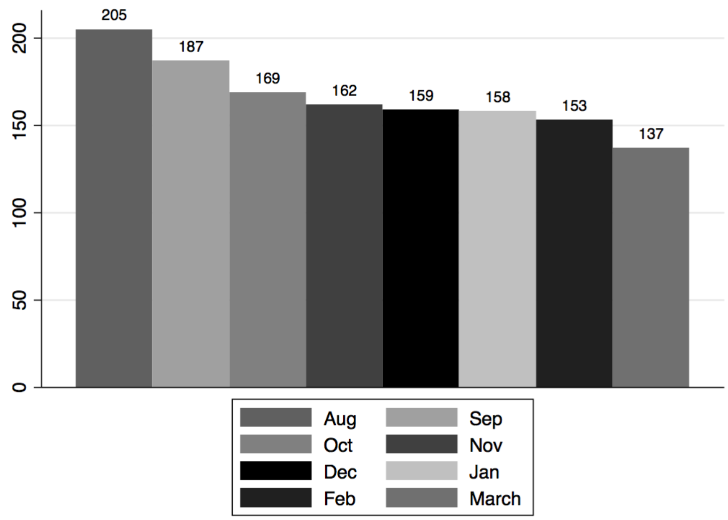
We are not suggesting that sensors should replace surveys or that they should or can be used in every study of technology adoption. Many questions about adoption, and the use and impact of new technologies cannot be answered with sensors alone. In addition, sensors still require careful and time-intensive field testing, as frequent failures still pose challenges in many studies, including ours (Wilson et al., 2016). Our results, however, highlight how sensors can provide more accurate and precise information. This seems particularly relevant when social desirability is expected to be high. While it might be too early to draw general conclusions, a number of studies, including ours, suggest that the overreporting of use is mostly a problem when adoption is low, and hence that it is particularly important to receive an objective measurement in such cases. We also observe that while survey and sensor measurements were similar on average, they did not agree for individual households. Hence, sensors might be particularly relevant when researchers want to conduct sub-group analyses or use smaller sample sizes. As for the survey design, we learned to not use skip patterns for important questions, as they might be misunderstood and valuable data lost. Furthermore, asking a few individuals within a household about the details of their use across the day did not provide more accurate answers than asking for a broader estimate (e.g., daily usage).

Finally, sensor data can help us better understand how to improve study and survey design, since they provide a credible benchmark to test different types of survey questions and interactions between surveyors and respondents.

3.6 Appendix

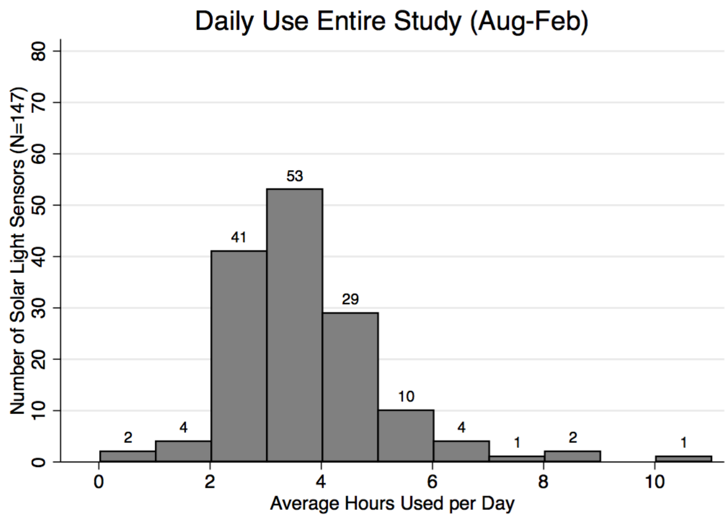
A. Additional Tables and Graphs

Figure A.1: Number of Working Sensors by the End of each Months



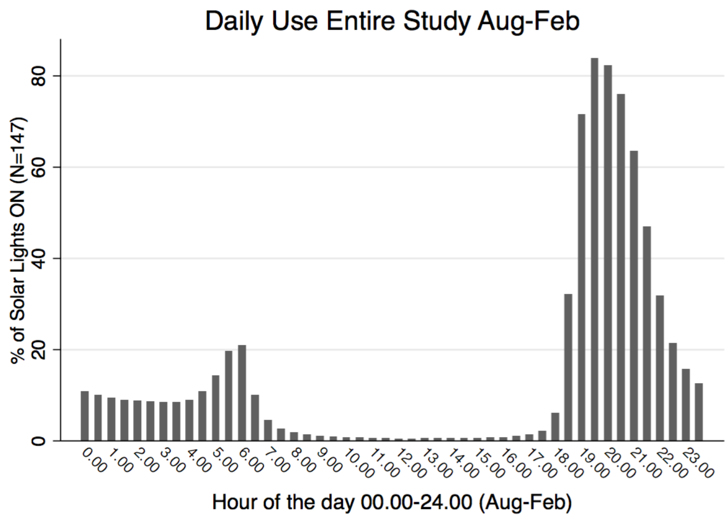
Notes: This graph shows the number of sensors that worked until the end of the indicated month.

Figure A.2: Average Hours Solar Lights are Used per Day (Aug-Feb)



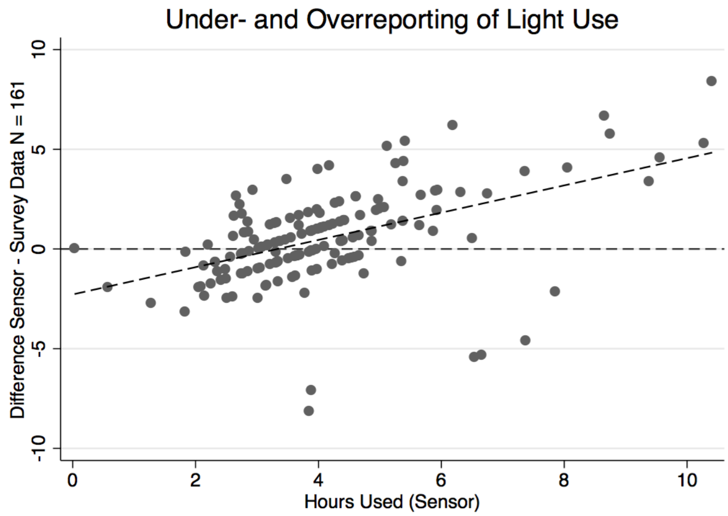
Notes: This graph shows sensor data about the average number of hours the solar lights were used per day during the entire study.

Figure A.3: Use Across the Day (Aug-Feb)



Notes: We classify usage by whether the solar light was used for more than 15 minutes without interruption during the relevant half-hour slot. We then calculated for each sensor the percentage of days that the light was on across all days that the sensor worked and then used this information to calculate the average across all sensors. Sample is restricted to sensors that worked until the end of the study.

Figure A.4: Under- and Overreporting of Use



Notes: This graph shows the correlation between the difference of sensor data and the survey data (Aggregated Question) and average hours used per day according to the sensor data. Positive values on the y axis indicate that respondents underreported use, while negative values suggest that they overreported use.

Table A.1: Use Across Months

	(1)
VARIABLES	Sensor Hrs
September	0.183
	(0.254)
October	0.387
	(0.239)
November	0.384
	(0.250)
December	0.246
	(0.240)
January	0.242
	(0.233)
February	0.302
	(0.233)
March	0.325
	(0.230)
Observations	1,096
R-squared	0.004
Mean Sensor	4.053

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Left out group is August. We first calculated the average use per month per sensor. Mean use is across all months.

Table A.2: Use Across Weekdays

	(1)
VARIABLES	Sensor Hrs
Tuesday	0.062*
	(0.032)
Wednesday	0.016
	(0.029)
Thursday	0.016
	(0.030)
Friday	-0.008
	(0.034)
Saturday	-0.096**
	(0.046)
Sunday	-0.174***
	(0.039)
Observations	959
R-squared	0.002
Mean Use	4.022

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Left out group is Monday. We first calculated the average use per weekday per sensor. Mean use is across all weekdays.

Table A.3: Use previous Month as Predictor for Survival

VARIABLES	(1) Sensor Hrs-Aug	(2) Sensor Hrs-Sept	(3) Sensor Hrs-Oct	(4) Sensor Hrs-Nov	(5) Sensor Hrs-Dec	(6) Sensor Hrs_Jan	(7) Sensor Hrs-Feb
Stopped Working in Sept	0.819						
	(0.538)						
Stopped Working in Oct		1.263**					
		(0.507)					
Stopped Working in Nov			-0.396				
			(0.268)				
Stopped Working in Dec				-2.237**			
				(0.971)			
Stopped Working in Jan					0.460***		
					(0.150)		
Stopped Working in Feb						-2.046**	
						(0.803)	
Stopped Working in March							0.031
							(0.482)
Constant	3.759***	3.828***	4.077***	4.095***	3.964***	4.041***	4.097***
	(0.148)	(0.160)	(0.146)	(0.161)	(0.150)	(0.143)	(0.154)
Observations	205	187	169	162	159	158	153
R-squared	0.013	0.031	0.002	0.022	0.000	0.040	0.000
N droped next Month	18	18	7	3	1	5	16

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Comparing Survey Data and Sensor Data

VARIABLES	(1) Sensor Hrs/ All Data	(2) Sensor Hrs/ All Data	(3) Sensor Hrs/ First Month	(4) Sensor Hrs/ First Month	(5) Sensor Hrs/ Yester-day	(6) Sensor Hrs/ Yester-day
Surv (Aggr.)	0.208***		0.317***		0.412***	
	(0.062)		(0.070)		(0.093)	
Surv (Detail)		0.064		0.107		0.097
		(0.083)		(0.096)		(0.124)
Observations	161	162	161	162	125	126
R-squared	0.066	0.004	0.114	0.008	0.138	0.005
Mean Sensor	3.706	4.067	3.864	3.864	3.706	3.706

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. We include sensor data over the entire study period where we have both survey measures.

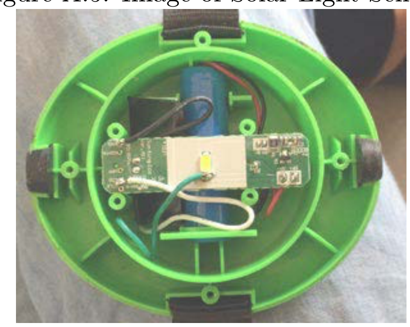
Table A.5: Difference in Reporting by Quintile

VARIABLES	(1) Diff Sens-Surv (All data)
Use 2nd Quintile	0.653
	(0.527)
Use 3rd Quintile	0.578
	(0.523)
Use 4th Quintile	1.811***
	(0.502)
Use 5th Quintile	3.071***
	(0.536)
Constant	-0.708*
	(0.373)
Observations	161
R-squared	0.213
Mean	3.985

Notes: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

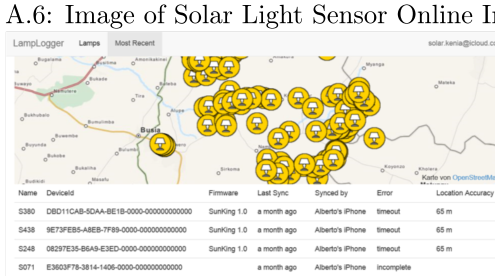
B. Pictures

Figure A.5: Image of Solar Light Sensor



Notes: This picture shows how the sensors were soldered inside the Sun King Eco Solar Light.

Figure A.6: Image of Solar Light Sensor Online Interface



Notes: This shows the online interface of the sensor data. On top is the map, which indicates the points where sensor data was collected. On the bottom there is information about the data collection organized by sensor identification number.

Figure A.7: Sun King Eco Solar Light

Figure A.8: Sun King Mobile Solar Light

C. Survey Questions

Aggregated Question:

- Do you own one or several lanterns? Options: yes/no
- Does any of your solar lanterns still work? Options: yes/no
- Yesterday, for how many hours did you use a solar lantern?
  Options: 0h-24h

Time Diary Questions:

- What did you do between XX:XX and XX:XX?

  Options: same as in previous time slot at work (non-agricultural work) barber/salon bathe, dress brewing alcohol care for children / sick / elderly clean, dust, sweep, wash dishes or clothes, ironing, other household chores cook, prepare food discuss activities of the next day with partner doctor/hospital visit eat farm work fetch water, firewood fishing or hunting Funeral/wedding activities help homework herding animals/ work with livestock listen to radio other religious activity (e.g. study, group) participate in community activities / meetings / voluntary work play sports pray prepare children for school read book repairs around / on home rest sewing/fixing clothes shop for family sleep socialize with other household members socialize with people outside of the household spend time with spouse / partner study / attend class travel by bicycle travel by foot travel by motorized means visit / entertain friends watch TV Other

- What lighting source did you use for this activity, if any?

  Options: Electricity powered lighting Solar home system powered lighting Tin Lamp Kerosene lantern/Hurricane Fire Wood Battery powered torch/lantern Candle Solar lantern/solar torch Pressurized Kerosene Lantern Other rechargeable lantern Cell phone light No lighting used Matchsticks Other.

Chapter 4

Indirect Effects of Subsidizing Green Technology in rural Kenya

Abstract: Subsidies can have a number of effects beyond their direct impact on take-up. On the one hand, they can lead to lower usage rates among adopters, since the psychological effect of paying less (sunk cost) might lead them to value the product less, or because subsidies may lead to poor targeting (selection effect). Temporary price reductions might also lead to an expectation of lower prices in the future (anchoring effect) and thus to lower demand in the long run. On the other hand, subsidies and subsequent increased adoption among a sub-group of households can affect adoption rates more generally, as people learn from or imitate early adopters (social interaction effects). While imitation effects would increase future adoption rates at any price level, the impact of social learning is ambiguous and may affect take-up differently at different prices. This paper presents results from a two-stage randomized control trial studying the direct and indirect effects of subsidies on the adoption of off-grid solar lights in rural Kenya. Random distribution of free solar lights during the first period created an exogenous variation in the number of adopters in the networks of the remaining participants, who, in the second period, received an offer to purchase a solar light at a high or a low price. We first show that subsidies sharply increase adoption without leading to lower use. Social interaction effects seem to increase the price sensitivity of demand, whereby demand increases among households that were offered a lower price, but tends to decrease among households that received the high price. These findings are thus consistent with social learning rather than imitation effects. Further our results suggest that network effects are complements rather than substitutes for subsidies.

4.1 Introduction

Why have cell phones spread so quickly in Sub-Saharan Africa, while other promising technologies (such as non-traditional cookstoves) have failed to take off (Aker & Mbiti, 2010; Hanna, Duflo & Greenstone, 2016; Miller & Mobarak, 2014; Suri & Jack, 2016)? Rapid technological progress has led to the development of products and services with the potential to improve the lives of millions of people in low and middle-income countries. However, these novel technologies can only make a substantial difference if consumers actually access them at a large scale and use them over extended periods of time.

Prices for off-grid solar technology have decreased dramatically in recent years, and solar now offers a promising solution to the 600 million people in sub-Saharan Africa who are still unelectrified (SEAll, 2017). In Chapter 2, we show that the use of solar lights leads to a reduction in kerosene use, which has important health and environmental effects. Access to a solar light also has some private returns, as it allows adopters to save 41.8% of what they would pay for their energy consumption otherwise. However, acquiring a solar light at market price requires a relatively large up-front investment of around 900 KES (US $9), corresponding to 12% of an average household's monthly expenditure. Less than 10% of households owned a solar light when we started the study (see Chapter 2). These findings support two arguments in favor of subsidies: first, using solar lights have positive health and environmental externalities at a relatively low cost. Second, a large share of the population in our setting would not be able to access this minimum level of modern energy without further price reductions.

However, to be an effective policy tool, subsidies have to significantly increase take-up without compromising use among those who receive or purchase the product. There are two effects that might lead to lower use among households that do not pay the full price: the "sunk cost effect", which suggests that a product purchased at a lower price might decrease a consumer's valuation of that product and thus their propensity to use it (Ashraf, Berry & Shapiro, 2010; Cohen & Dupas, 2010; Dupas, 2014; Thaler, 1980) and the "screening effect", which implies that the full price helps ensure that only households which truly value and use the product will purchase it. With the latter, subsidies could encourage people who do not need it to purchase it anyway (Ashraf, Berry & Shapiro 2010; Dupas, 2014). Thus, both effects could lead to lower usage among recipients of the free or subsidized technology.

In addition, subsidies and the subsequent increase in adoption, might lead to social interaction effects (or network effects), which could influence adoption. Following the terminology put forward by Manski (2000), we suggest two different types of social interaction effects that seem to be relevant here:[41]

The first is related to the idea that one might get some sort of social value when imitating others or following a trend (Bandiera & Rasul, 2006; Banerjee, 1992; Manski, 2000). While few experimental studies in developing countries explain their findings with this mechanism, Benard & Torero (forthcoming) argue that some sort of pressure "to keep up with your neighbor" is most likely what drives the increase in take-up of grid connections among households that live next to estates which were recently connected to the grid in Ethiopia. The authors find that every additional close neighbor (within a 30 m radius) led to a 4 percentage-point increase in the connection rate.

The second type of social interaction effect relates to social learning. Here, non-early-adopters update their beliefs about the costs and benefits of a new technology based on what they learn from early adopters. If they learn that private returns are higher than expected (or costs are lower), social learning makes non-early-adopters more likely to adopt. If private returns are lower than expected, social learning might reduce take-up. This was the case with deworming, where social returns were very high, while (immediate) private returns were not (and arguably lower than expected). Thus, social learning lowered adoption (Kremer & Miguel, 2007). Drawing on the same concepts, Miller & Mobarak (2014) show that take-up of non-traditional cookstoves decreased as people learned about their limited private returns. Similarly, Dupas (2014) argues that while social learning initially had a positive effect on the adoption of bed nets, the social learning effect reversed over time as private returns to bed nets decreased. Devoto et al. (2012) suggest that the increase in the take-up of piped water in urban Morocco within a close proximity to households who already had piped water was caused by people who learn from their neighbors' surprisingly high private returns. The same argument is put forward by Conley and Udry (2010), who explain the diffusion of a new agricultural technology in Ghana with social learning about its high returns. In a study about menstrual cups in Nepal, Oster & Thronton (2012) suggest that peers learn how to use the

[41] These differentiation is based on Manski (2000). He mentions a third effect "constraint interactions" whereby actions of others influence the choices available to other agents. He uses road congestions as an example whereby an individuals depends on the travel time needed, which is a function of everyone else's turn. However, this type of interactions does not seem applicable in our setting.

new technology from each other. In the above-mentioned cases, social learning is shown to have positive effects on adoption if people learn that the private returns are larger than expected. Similarly, negative effects can be expected when private returns are smaller than anticipated.

An additional aspect of social learning, one that has received less attention in the literature, is that the new information can also change the elasticity of demand and thus the effect of subsidies. In theory, this effect can go in both directions: on the one hand, new information can increase the dispersion of consumers' valuations (compared to their valuations before the additional exposure) and thus decrease price elasticity (Ashraf, Jack & Kamenica, 2013; Caswell & Mojduzka, 1996). This could be the case if the private returns of a product are more heterogenous than people previously thought. On the other hand, additional information can also reduce the heterogeneity of people's valuations of the product and consequently make demand more sensitive to price. In addition, more information can diminish the signaling effect that a price has in the absence of information, also increasing price elasticity. This is what Ashraf, Jack & Kamenica (2013) find when looking at the interaction of information and subsidies for an unfamiliar water-purification product in Zambia. How additional information (gained through social interactions in our case) affects price elasticity thus remains an empirical question (Ashraf, Jack & Kamenica, 2013).

Increasingly, researchers go beyond simple measures of numbers or shares of adopters within one's network and aim to understand the structure and the qualities of networks (see Maertens & Barret, 2012 and Breza, 2016 for an overview). Part of this literature focuses on the role that particularly well-connected individuals (or entry points) can have for the adoption rate within the entire network (Beaman et al., 2015, Banerjee, 2013; BenYishay & Mobarak, unpublished).

In this paper we aim to parse out different indirect effects of subsidies on adoption. We first describe the direct effect of subsidies on demand. Second, we study the effects of price on usage, comparing participants who received high-priced, low-priced, and free lamps. Our research design does not allow us to differentiate between selection and sunk costs effects as the causes behind possible differences in usage. Third, we look at whether social interaction effects increased adoption and how they interact with subsidies. We use different measures of social interaction effects based on geographic proximity and network structure. As in most other studies on social interaction effects, we are unable to formally test whether imitation or learning new information is the mechanism driving these effects. However, since we only find positive social interaction effects when combined with subsidies (see next paragraph), and negative ones otherwise, our results are more consistent with social learning about limited social returns. Finally, we provide suggestive evidence about potential price anchoring effects stemming from subsidies.

We conducted a two-stage randomized price experiment with over 1,400 households in the rural areas surrounding the town of Busia in western Kenya. We sampled households from 20 primary schools. In each school, a randomly selected group of households received a free solar light at baseline (first stage). A separate group received a voucher to purchase a solar light at a higher price (US \$9 /US \$7) or at a lower price (US \$4), which they could redeem within four to six weeks (second stage). The free distribution of solar lights in the beginning of the study generated an exogenous shock of increased adoption in respondents' network. We could then measure how this random increase in adoption in respondents' networks influenced their purchase decision. This design allowed us to measure network effects and avoid many typical identification problems (Manski 1993, 2000). In addition, our research design allows us to study how this exogenous increase in adoption within respondents networks interacts with subsidies. We study individuals' networks in two different ways, defining them as individuals' neighbors (i.e. people who live in a certain radius) and as people who live in the same village. We also test whether the most central person in the village received a free solar light by random chance. Initially, we planned to conduct a second price experiment during endline to measure anchoring effects. Unfortunately, we were not able to complete this experiment as our partner organization and supplier of solar lights unexpectedly stopped working in Kenya.

Looking at the direct effect of subsidies, we find that demand for solar lights is very price elastic: a subsidy of 56% (compared to the market price) led to a 40 percentage-point increase in take-up. Second, we find that full subsidies (i.e. free solar lights) do not affect the intensity of use, but that higher subsidies increase children's use of solar lights. There is some evidence of social learning, as respondents who live in villages with a higher number of people receiving a free solar light (or respondents who know more such people) are more likely to purchase a solar light - if (and only if) they received a high subsidy. For households that received a large subsidy, having an additional adopter in the village led to an increase in the likelihood of adoption of 1.2% (the average number of adopters per village was 7 (SD 5.1)). Whether the most central person received a free solar light had no effect on adoption rates. Living in proximity to a higher number of free solar light recipients even reduced the likelihood of adoption by households which could only purchase a solar light at a higher price. Consequently, social interaction effects only seem to increase adoption if combined with subsidies. These findings suggest that social interaction effects and subsidies complement each other. Our results are consistent with a story in which recipients learn about the limited extent of the private returns, making the investment worthwhile at low price, but not necessarily at a high price. While our data on price anchoring is limited, we do not find evidence that anchoring effects influenced revealed willingness to pay.

Our work builds on a handful of recent studies about the direct effects of subsidies on the demand for solar lights (Grimm et al., 2016b; Niccolò et al., unpublished; Yoon, Urpelainen & Kandlikar, 2016). In all cases, the research team played an auction game and found very low willingness to pay for solar lights, even at highly subsidized prices. Instead of this approach, we randomize prices for solar lights at the household level, a more intuitive approach than bidding games that also more closely reflects how our partner organization and other enterprises operate. Moreover, our study goes a step further by studying the indirect effects of subsidies on take-up in future periods. We further expand on existing work by estimating the impact of subsidies on technology use and intra-household allocation.

Beyond studying the specific case of solar lights, we hope to contribute to the literature about complex and sometimes contradicting effects of subsidies on the adoption of technologies with positive externalities (Ashraf et al., 2010; Cohen & Dupas, 2010, Kremer & Miguel, 2007). Relatedly, we add to the discussion about how subsidies interact with additional information or exposure to the product (Ashraf, Jack & Kamenica, 2013). Finally, we make a contribution to the literature that uses randomized designs to understand the diffusion of technology in developing countries (see Devoto et al., 2012; Dupas, 2014a; Kremer & Miguel, 2007; Oster & Thronton, 2012 for example) and of modern energy access in particular (Benard and Torero, forthcoming).

This field experiment was registered on the AEA website and preceded by a pre-analysis plan. The hypotheses we tested that related to network effects and anchoring were not part of the initial analysis plan, however.

4.2 Study Design and Data

Study Design

This study is part of a larger randomized control trial (RCT) conducted between June 2015 and March 2016 in Nambale and Teso-South, two sub-counties located in Busia, in western Kenya. In this section, we only explain the aspects of the RCT that are relevant for the analysis of adoption; more information about the overall study can be found in Chapter 2. We randomly selected 10 schools[42] in each of the sub-counties and drew a random sample of 1,410 households that had at least one pupil in class five, six, or seven in one of the selected schools. Nine respondents chose not to participate in the study, leaving us with 1,401 households. At endline, we were able to interview 1,313 (93.7%) of the adult respondents.

The randomization of actual offers was conducted at the household level and stratified at the school level. Sampled households were assigned to one of the following groups:

1. Control group: 20 households per school, 400 households total, did not receive any intervention.

2. Free solar lights group: 20 households per school, 400 households total, received a free solar light. Solar lights were handed out during baseline.

3. Offer to buy group: About 30 households[43] per school, 610 households in total, received a voucher to purchase a solar light at one of the following prices: low Price of 400 KES /US $4 (N=209), High Price of either 700 KES/US $7 or 900 KES/US $9 (N=401). We combined the two high prices to keep the analysis more tractable and because ownership at endline was the not differ significantly between the two prices. Moreover, prices for solar lights have further decreased since the end of the study, and today both prices could be considered market price.

[42] The local administration provided a list of all 127 public schools (50 in Nambale and 77 in Teso South), a number of schools were eliminated, such as schools with less than 100 pupils, schools with only girls or only boys, boarding schools, schools located in urban centers, too far from the research office to be easily reached, and schools whose head teacher was not present at the term head teacher meeting. From the remaining 97 schools, 20 were selected at random (10 in each sub-county).

[43] Two of the schools did not have enough households that met the selection criteria. In these two schools, we reduced the number of vouchers distributed to 0 (Sango) and to 10 (Aburi) and increased the number of sampled students in larger schools instead.

Free solar lights were handed out during baseline. The sale of solar lights to those who received an offer to buy were conducted as follows: field staff gave respondents a voucher that indicated the relevant price offer. Surveyors showed respondents the type of light they could purchase and explained the main features of the lights (see script in the Appendix, Section C). Respondents could then redeem their voucher at the office of their child's head teacher within a period of four to six weeks after baseline, as this was how our partner organization handled sales in their program. We then collected data from respondents who redeemed the vouchers at the point of sale (Figure 4.1).

Figure 4.1: Study Timeline

../../3_Paper/graph_timeline.png

Data

Prior to commencing with the full study, we conducted a number of in-depth interviews with solar light users, non-users, and teachers, as well as field staff and executives from our study partner, SunnyMoney. We also held five focus group discussions with users and non-users of solar lights. The information from the in-depth interviews and focus groups was used to design the survey instruments. Quantitative data used in this study are a baseline survey conducted in June/July 2015 and an endline survey conducted seven months later. During each survey round we interviewed the sampled pupil as well as their main caretaker. Social network data were only collected during endline (the specific questions asked in the survey can be found in Section B of the Appendix). In addition, we placed a surveyor at the solar lights sales points to keep track of all sales and to ensure that the vouchers were redeemed correctly. More details about the data collected can be found in Chapter 2.

The study was conducted in rural areas of western Kenya, where households spend an average of US $73.20 in cash per month. A typical sampled household has 6.7 members, with 4.3 children under the age of 18. Most live in simple housing with earth floors (88.3%) but could afford iron sheet roofs (64.6%) over their main building. Typically, a household head had attended school for 6.4 years. At baseline, most households (88.4%) rely primarily on small locally-produced kerosene lights (tin lanterns) for lighting. Others use larger kerosene lanterns (5.3%), or solar lights (3.8%); only 1.1% use electricity-powered lighting as their primary lighting source. An average household spends around US $3.61 (KES 360.9) per month on energy, corresponding to 4.9% of the household's total cash expenditure. A table showing baseline characteristics and balance between treatment groups can be found in the Appendix (Table A.1).

Estimation of Network Effects

The study design described in the previous section allows us to circumvent many of the problems typically associated with analyzing social networks; namely, that there may be omitted variables, whereby people who know each other are just similar and adoption decisions correlate due to these similarities. Respondents might also exchange information, observe each other's behavior, or change their behavior simultaneously, creating a "reflection problem" which makes it hard to establish causality (Manski, 1993). For these reasons, we exploit the fact that we first distributed free solar lights to a random sub-sample and thus generated a sudden exogenous increase in solar light adopters in other individuals' networks. Afterwards, in the first four to six weeks after baseline, different households received offers to purchase a solar light (Figure 4.1). We thus analyze whether and how this sudden increase affects people's decision to adopt.

We looked at individuals' networks in two ways commonly used in the literature. First, we identified households' GPS location, allowing us to see who lives in their vicinity. Second, we recorded the village in which they lived. We then asked respondents if they knew each other respondent (by cycling through all other respondents from the "free" and the "offer to buy" groups) in their village, and, if so, how well.

Based on this information, we constructed two variables: the number of free recipients in respondent's village, and the number of free recipients in the village acquainted with the respondent. Second, we calculated two additional measures with the number of free solar light recipients living within a radius of 250 and 500 meters around their estate respectively. We also constructed a variable to identify how influential different individuals within a network might be. While there are a number of different ways to measure influence, we chose to simply rank all individuals by number of links and identify the person in each village with the most connections. We then created a measure that indicated whether this person, by random chance, received a free solar light at the beginning of the study. Finally, to understand how social interactions affects the demand curve, we interacted these network measures with the different subsidy levels.

We focus on geographic proximity for a number of reasons. First, various studies have found that information is often exchanged at the village level (Besley & Case, 1997; Foster & Rosenzweig, 1995; Munshi, 2004). In fact, data from the same context reveal that rural households communicate frequently with their neighbors (Dupas et al., 2012). Second, information gathered from qualitative interviews also showed that people living within geographic proximity of one another are important sources of information. Finally, during baseline, 67.4% of those who had previously seen a solar light indicated that they had seen it at a neighbor's house, implying that neighbors are important in that regard. Ideally, we would control for the village size in the regressions that are based on the number of recipients of free lights in the respondent's village. Unfortunately, however, we do not know how large the sampled villages are, which we will discuss further in the next section.

Estimation Approach

We used the following equation to estimate demand at different price levels:

$$Ownership_{ij} = \alpha_0 + \sum_{k=1}^{3} \alpha_k(offer_{ij}) + \lambda_i + \epsilon_{ij} \tag{3}$$

$Ownership_{ij}$ designates whether a household i in school j owned a solar light at endline (or purchased a solar light using their voucher), α_0 indicates the take-up level of the control group, and α_k shows take-up at the different price levels.

$Offer_{ij}$ is a set of dummies for the price level at which a household received a voucher to purchase a solar light (free, 400 KES or US \$4 (low price), or KES 700/900 or US \$7/9 (high price)).

λ_i refers to school fixed effects and ϵ_{ji} is an error term.

For the analysis of network effects we focused on households in the control group and those who received an offer to purchase one. The following equation was used to estimate network effects at different price levels:

$$Ownership_{ij} = \alpha_0 + \sum_{k=1}^{2} \alpha_k(offer_{ij}) + \beta(NetworkAdoption_{ij}) + \sum_{k=1}^{2} \gamma_k(offer_{ij} * NetworkAdoption_{ij}) + \delta X'_{ij} + \epsilon_{ij} \quad (4)$$

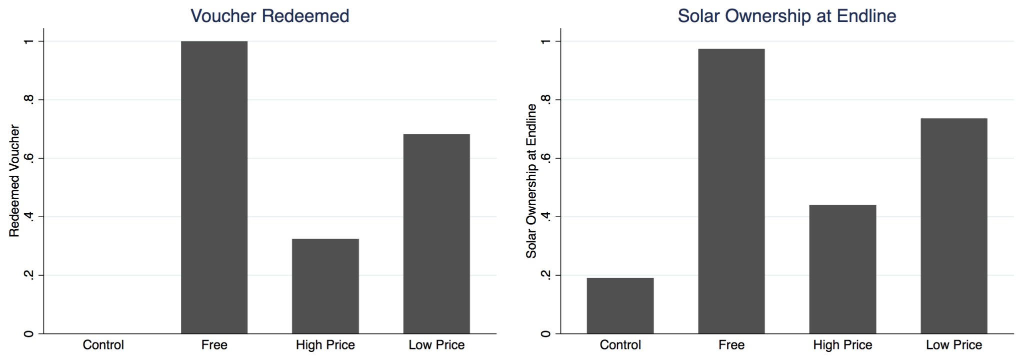
$NetworkAdoption_{ij}$ refers to the number of people in individual j's network i who received a free solar light (or whether the most central person received a free solar light). $Offer_{ij}$ is a set of dummies for the price level at which a household received a voucher to purchase a solar light (400 KES or US \$4 (low price), or KES 700/900 or US \$7/9 (high price)). X_{ij} refers to solar light ownership at baseline. We also control for network size, where possible (e.g. we control for the number of people living within a certain radius). One data limitation we have is that we do not know the size of the sampled village, only the number people we sampled from said village. We provide the relevant regressions while controlling for this measure in the Appendix. The remaining variables are the same as above. In this equation, standard errors are clustered at the village level.

4.3 Results

4.3.1 Direct Effects of Subsidies on Demand and Use

In this section we test whether subsidies increase take-up and whether they affect use. We find that households respond strongly to price changes. While everyone took up the offer of a free light, only 68.2% purchased one at the highly subsidized price of KES 400, or US \$4. Take-up decreased to 32.4% when the price was high (Figure 4.2). In the graph on the right, we look at solar light ownership at the end of the study, independently of wether respondents purchased the solar light through our study or elsewhere. Again, we observe that households that received a free light or an offer to purchase a light at a high subsidy were much more likely to own one at endline (Figure 4.2). In this regard, subsidies are a powerful tool to increase adoption among their beneficiaries.

Figure 4.2: Effect of Prices on Take-Up



Notes: The first graph from the left shows the share of redeemed vouchers within our program at different prices (N=1'411). The second graph shows the share of respondents who owned a solar light during endline no matter where they got the solar light from (N=1'314). The same data were used in Chapter 2.

Table 4.1: Solar Light Use at Endline

VARIABLES	(1) Solar Use Total (Hrs)	(2) Solar Use Adult (Hrs)	(3) Solar Use Pupil (Hrs)	(4) Main User Pupil
Free	Ref	Ref	Ref	Ref
Low Price	-0.080	0.011	-0.020	-0.001
	(0.194)	(0.132)	(0.131)	(0.045)
High Price	0.084	0.177	-0.120	-0.098**
	(0.189)	(0.138)	(0.125)	(0.049)
Observations	620	673	620	548
R-squared	0.019	0.021	0.004	0.013
Controls	YES	YES	YES	YES
Mean Free	6.676	3.072	3.550	0.762

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include solar ownership, kerosene spending and grid connection at baseline.

Second, we compare the use of the solar light by households that received a free light, those that paid the low price, and those that paid the high price. As previously explained, the fear is that subsidies could lead to over-inclusion of households that will not actually use the solar lights, or that paying less makes people value and use the product less (sunk cost effect). We follow Dupas' (2014) approach and limit the sample to adopters, testing whether those who paid a higher price use the solar light more compared with those who received one for free.

There are no statistically significant differences in the number of hours that adults and children report using the solar lights (Table 4.1 Columns 1-3). However, there seems to be a shift in terms of who uses the solar light, as children are given higher priority when respondents receive a free solar light or a high subsidy (Table 4.1, Column 4). This result relates to research on the effect of subsidies on intra-household allocation. A study by Hoffman (2009), for example, finds that bed-nets were more likely to be used by children when they were distributed for free. This finding is weakly supported by the fact that the (non-significant) point estimates for children's reported use get smaller with increasing price, while getting larger for adults (Table 4.1, Column 2 and 3).

In summary, we find that subsidies strongly increase uptake. We do not find that recipients of free or highly subsidized solar lights use them less. In fact there might even be a small shift within the households, where children, for whom positive effects in terms of health and education are largest use them more (Chapter 2 discusses impacts of solar lights for adults and children in detail).

4.3.2 Indirect Effects of Subsidies on Demand

Subsidies and Network Effects

As discussed above, short-term subsidies can lead to social learning when people learn from early adopters' experiences and update their beliefs about the costs and benefits of solar lights. In addition to affecting overall demand, additional exposure could also change the shape of demand curve. Alternatively, latecomers may imitate early adopters to conform, gain social status, or earn some other form of social utility.

Table 4.2: Network Effects: Summary Statistics

	(1) Mean (SD)	(2) Min-Max	(3) Obs
# in village	26.511 (13.907)	0.00- 52.00	933
# in village (free)	7.048 (5.142)	0.00- 51.00	934
# FR knows	9.698 (6.497)	0.00- 33.00	933
# FR knows (free)	3.110 (2.667)	0.00- 14.00	933
# in 500m	9.108 (5.235)	0.00- 26.00	934
# in 500m (free)	2.639 (2.116)	0.00- 15.00	934
# in 250m	2.650 (2.152)	0.00- 12.00	934
# in 250m (free)	0.764 (0.973)	0.00- 5.00	934

Notes: All variables refer to the number of sampled households within village or radius of 500m/250m.

In the first part of the analysis we look at different types of networks in which these effects could play a role, namely whether households live in the same village and their geographic proximity. To give the reader a sense of the structure of these networks we summarize their key features.
Each village had an average of 26.5 sampled households (SD 13.9), of which 7 (SD 5.1) households received a free solar light. On average, respondents knew 9.7 other respondents in their village (SD 6.5), and 3.1 (SD 2.7) who received a free solar light. At the village level, we use three different measures: first, we focus on the number of recipients of free solar lights in each village. Second, we use the number of recipients of free solar lights that the respondent knows, and third, whether the person in the village with the most connections to other villagers had received a free solar light (Table 4.2). Our fourth and fifth network measures focus on everyone in the sample living within a radius of either 250m or 500m around the respondents. On average, a respondent had 9.1 (SD 5.2) neighbors living within a radius of 500 m, 2.6 (SD 2.1) of whom received a free solar light, and 2.7 (SD 2.2) other study participants within 250m, of whom 0.8 (SD 1) received a free light (Table 4.2).

To understand whether and how network effects affect demand at different price levels we show how network effects interact with price subsidies in Table 4.3. The omitted group is the control group in all regressions, and the outcome of interest is ownership of a solar light at endline. Table 4.3, Column 1 shows the direct impact of price on take-up. Unsurprisingly, price has a very strong effect on take-up regardless of which specification we consider. Having an additional person in me's village who received a free solar light increases respondents' propensity to adopt by 1.2 percentage-points if the respondents themselves received an offer to purchase a solar light at a low price (Table 4.3, Column 2). Recall that each village had an average of 7 households which received a free solar light. Note, however, that we were not able to control for village size in this regression, as we do not have this data and therefore we cannot exclude that this effect is at least partially driven by village size.[44] To put this result in perspective, this effect is around half the effect size reported by Bernard & Torero (forthcoming) for the

[44] In the Appendix table A.2 we show the regression with controlling for sampled households in the village as a proxy for village size. While the coefficient remains similar in size it becomes statistically insignificant.

Table 4.3: Network Effects at Different Price Levels

VARIABLES	(1) Ownership	(2) Ownership	(3) Ownership	(4) Ownership	(5) Ownership	(6) Ownership	(7) Ownership
# in village (free)		-0.002					
		(0.004)					
# in village (free) * Low Price		0.012**					
		(0.006)					
# in village (free)*High Price		-0.003					
		(0.006)					
Low Price	0.536***	0.448***	0.449***	0.507***	0.507***	0.585***	0.545***
	(0.037)	(0.067)	(0.071)	(0.055)	(0.053)	(0.062)	(0.047)
High Price	0.246***	0.267***	0.263***	0.250***	0.273***	0.365***	0.299***
	(0.032)	(0.057)	(0.052)	(0.035)	(0.037)	(0.051)	(0.042)
# FR knows (free)			-0.002				
			(0.008)				
# FR knows (free) * Low Price			0.027*				
			(0.014)				
# FR knows (free) * High Price			-0.007				
			(0.011)				
Central Person (free)				-0.050			
				(0.049)			
Central Person (free) * Low Price				0.064			
				(0.087)			
Central Person (free) * High Price				-0.010			
				(0.068)			
Central Person (free known)					-0.015		
					(0.042)		
Central Person (free known)* Low Price					0.082		
					(0.081)		
Central Person (free known) * High Price					-0.079		
					(0.062)		
# in 500m (free)						0.010	
						(0.009)	
# in 500m (free)* Low Price						-0.019	
						(0.019)	
# in 500m (free)* High Price						-0.047***	
						(0.015)	
# in 250m (free)							0.019
							(0.022)
# in 250m (free)* Low Price							-0.015
							(0.037)
# in 250m (free)* High Price							-0.076**
							(0.034)
Observations	933	934	930	934	934	934	934
R-squared	0.215	0.209	0.209	0.208	0.209	0.216	0.210
School FE	NO	NO	NO	NO	NO	NO	NO
Controls	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES
Mean Control	0.190	0.190	0.190	0.190	0.190	0.190	0.190

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control group is omitted in all regressions. The outcome is ownership of solar light at endline. Controlled for solar ownership at baseline. In Columns 3 and 5 we control for total nr of people the respondent knows within the village, in Columns 6-7 for total nr of sampled households in the respective radius. Appendix A.2 shows Columns 2-5 when controlling for nr of sampled households in the village.

probability of establishing a grid connection for each additional neighbor living within a radius of 30 meters. Our effects also seem relatively small compared to what the study on water connections in Morocco finds, which suggest that households within 20 meters of a treatment household were 18 percentage-points more likely to have bought a water connection at endline (Devoto et al., 2012). These network effects were only present if combined with a high subsidy.

When we restrict our network to people who live in the same village and are known by the respondents, we see the same pattern: there is a marginally significant increase in the probability of purchasing a solar light for recipients of the low price offer, but not for recipients of the high price or the control group (Table 4.3, Column 3). In this regression we control for the total number of people that the respondents knows. The next two regressions focus on the most central person in the network (the person with most social ties) and whether she received a free solar light. While none of these coefficients are significant, they point in the same direction: recipients of the low price offer tend to be more likely to adopt if the most central person in their network received a free solar light, while those who did not receive the low price offer did not. Finally, when we look at people living in the closest proximity to the respondent, we find that knowing more people who received a free solar light decreased the likelihood that recipients of the high price offer would purchase a solar light (Table 4.3, Column 6 and 7). This result is robust both for radii of 250m and 500m. In these regressions we control for the number of respondents within the respective radius.

To summarize, our results suggest that social interactions might slightly increase take-up when combined with high subsidies, but they do not affect take-up - and may even reduce it - if the solar light was offered at a high price. In that sense social interaction effects make demand more sensitive to price changes. These results are consistent with a story in which respondents gain more information about the relatively homogenous and somewhat limited private returns, which make the investment clearly worthwhile at low price, but not necessarily at a high price. An alternative explanation would be that the additional information they gain through their increased exposure to solar lights might also reduce the signaling effects of the price. We believe that this is less likely in our case, however, since respondents knew that they were being offered a temporary "special offer" and hence it seems less likely that they inferred information about the quality of the product from the price. A consequence of both of these mechanisms would be that respondents' beliefs about the returns of solar lights become more homogenous and thus more sensitive to price changes. While the increased adoption for the low price group could also be explained by imitation effects, a reduction in take-up among those who received an offer to purchase a solar light at a high price cannot be explained with this mechanism. Therefore, imitation effects seem less likely to explain our findings.

Price Anchoring Effects

A commonly cited fear is that temporary subsidies could lead people to lower their reference price for that product, making them unwilling to purchase the product at the market price in the future. Consumers may even become less likely to purchase other goods as they get used to "handouts". In this regard, price anchoring effects are an argument against temporary subsidies (Dupas, 2014; Koszegui & Rabin, 2006; Kremer & Miguel, 2007).
During baseline, we gave respondents a first random "anchoring" price for the solar light between KES 100 or US $1 and KES 1'000 or US $10 and asked if they were willing to pay that amount for the solar light. Then they received a second offer, also at random, to purchase the solar light within the next four to six weeks. Our results suggest that this first, random "anchoring" price did not influence their actual purchasing decision. It did also not matter whether the "anchoring" price was above or below the price they received later (Table 4.4, Columns 1-3).

We are aware that this is not an ideal setting, and that respondents might react differently if they encountered price increases in the real world. For this reason we planned an additional experiment during endline which, unfortunately, we were unable to conduct for logistical reasons.[45] However, we were still able to ask respondents who received a free solar light, received a low or a high price offer, or were part of the control group to estimate the market price of a solar light. There was no difference between the answers from the control group and respondents who received a high price. Interestingly, receiving a free solar light also had no effect on their price estimate (Table 4.4, Columns 4 and 5), suggesting that free distribution did not change people's price expectation. Receiving a free solar light also did not lower respondents stated willingness

[45] SunnyMoney, out partner organization and supplier of solar lights unexpectedly ceased operations in Kenya.

Table 4.4: Price Anchoring Effects

VARIABLES	(1) Voucher Redeemed	(2) Voucher Redeemed Low Price	(3) Voucher Redeemed High Price	(4) Price Est. (USD) Adopters	(5) Price Est. (USD) All	(6) WTP Solar (USD)
Offer Low Price	0.358***			-2.881**	-2.876***	
	(0.041)			(1.229)	(0.981)	
Anchor Price below Offer		-0.009	-0.037			
		(0.049)	(0.050)			
Offer High Price				-0.885	-1.277	
				(1.370)	(0.749)	
Free Solar Light	-	-	-	0.744	0.898	0.841*
				(1.056)	(0.762)	(0.438)
Control Group	-	-	-	Ref	Ref	Ref
Observations	600	210	401	577	917	358
R-squared	0.130	0.000	0.001	0.024	0.021	0.016
School FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Mean	0.477	0.477	0.477	14.14	13.72	8.219
Number of Schools	20	20	20	20	20	20

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controlled for solar ownership at baseline. For Column 4 and 5, the question was: "What is the price for the most affordable solar lantern available?" For Column 6, the question we asked was: "What is the maximum you would be willing to pay for this solar light?".

to pay, if anything it marginally increased (Table 4.4, Column 6). However, beneficiaries who received an offer to purchase at a low price did update their believes about the market price, estimating it to be US $2.88 lower than the control group (Table 4.4, Column 4 and 5). This is true for both those who decided to purchase a solar light (Table 4.4, Column 4) and those who did not (Table 4.4, Column 5). This could be because the temporary lower price anchored recipients' expectations.

However, the high subsidy group's price estimate was still US $11.1 (SD 7.0), which is higher than the price for solar lights found at local markets. Therefore, there is an alternative mechanism that could explain lower price estimates from the group that received an offer to purchase at a low price. Respondents who received a tempting offer may have started to collect more information about the market price and the product outside of the project and updated their expectations accordingly. Recipients of free solar lights and respondents in the control group had no incentive to do the same, since they were not faced with a choice one way or another. Perhaps fewer people from the high price group looked for additional information, since most of them had already made up their mind anyway. Unfortunately, we cannot distinguish between these two possible mechanisms.

In summary, we find no evidence that free distribution of solar lights leads to lower price estimates or lower stated willingness-to-pay in the future, but our data suggest that high subsidies do lead to lower price estimates. As price expectations were very high to start with, households who received a large discount had more realistic expectations at endline. However, we do not know if this effect was driven by price anchoring, better information, or other channels.

4.4 Conclusion

In this paper, we discuss whether and how subsidies for solar lights affect adoption in the short-term and how indirect effects might influence adoption in the long-run. We find demand for solar lights to be highly elastic with respect to price changes. Furthermore, our data suggest that recipients of free or highly subsidized solar lights do not use them less than those who paid the full price. Hence, we do not find evidence for selection or sunk-cost effects. Rather, our results suggest that children tend to use the solar lights more if they are distributed for free. With these findings, we expand the literature on how subsidies of products and services with positive externalities affect adoption, and in particular how subsidies influence intra-household allocation (Ashraf, Berry & Shapiro, 2010; Cohen & Dupas, 2010; Dupas 2014; Hoffmann, 2009). More specifically, we add to the literature on demand for household energy products, in particular off-grid solar lighting (Grimm et al., 2016b; Niccolò et al., unpublished; Yoon, Urpelainen & Kandlikar, 2016).

In addition to these direct effects, we find some evidence that network effects can reinforce the effect of subsidies, as we see that those who receive an offer to purchase a solar light at a low price tend to be more likely to take that offer up if they have more people in their network who (randomly) received a free solar light in an earlier period. However, social interaction effects have no effect and, in some specifications, even a negative impact on those who face high prices. Taken together, these results suggest that social network effects tend to increase price elasticity of demand. In terms of magnitude, the effect sizes are modest: for someone who is offered a solar lamp at a low price, the presence of an additional person who had received a free solar light in the same village increases the likelihood of purchasing a light by 1.2 percentage-points. This effect size is around half of what Bernard & Torero (forthcoming) find for the case of neighbors living within 30m of each other who get connected to the electrical grid. Even larger network effects were found in Morocco, where being within 20 meters of at least one treatment household increased the chances of choosing to connect to the grid by 18 percentage-points (Devoto et al., 2012).

While we cannot formally test the mechanisms that drive these effects, the results are consistent with a story in which respondents learn from their peers about the somewhat limited private returns of solar lights, which reduces the heterogeneity of their valuation. In that sense, social learning makes it increasingly clear to respondents that the private returns of a solar light make it worthwhile to purchase at a low price, but not necessarily at a high price. Alternatively, social learning about the quality of the product might also decrease the signaling effects of prices. Both of these mechanisms could explain the observed increase in the price elasticity of demand. Consequently, our study comes to a similar conclusion as Ashraf, Jack & Kamenica (2013), who find in their study of water-purification products in Zambia that subsidies and information (in our case social learning) complement each other when it comes to stimulating demand.

Our study also contributes to the literature that seeks to understand social networks and how to harness their power for the introduction of novel technologies in developing countries (see Breza, 2016 for an overview). In particular, our finding that network effects may increase price elasticity of demand may help explain some of the seemingly contradictory results in that literature. In the case of improved cookstoves, for example, some studies find positive social interaction effects (Bonan et al., working paper), while others find no, or even negative, effects (Beltramo et al., 2015; Miller & Mobarak, 2014). If social network effects indeed increase price elasticity for certain types of goods, it makes sense that they would increase or decrease demand depending on how the price relates to people's updated valuation. In our two-stage experiment we were able to test the effects of social interactions at different price points, which allowed us to analyze how social learning can change the shape of the demand curve.

A growing body of evidence suggests that social and dynamic effects on technology adoption can be large (Bandiera & Rasul, 2006; Banerjee et al., 2013; Bernard & Torero, forthcoming; Conley & Udry, 2010; Devoto et al., 2012; Dupas, 2014a; Foster & Rosenzweig, 2010; Kremer & Miguel, 2007; Miller & Mobarak 2014, Munshi, 2004; Oster & Thronton, 2012). So far, most field experiments randomized price in period one and measured network effects on the control group in period two. We propose that there might be important interaction effects between network effects and subsidies in subsequent periods, similar to the findings of Ashraf, Jack & Kamenica (2013) for the case of interaction effects between information and subsidies. For this reason we propose that further studies analyze multiple periods of subsidy provisions. This would allow researchers to see how subsidies in one period affect take-up in subsequent periods. Finally, it seems that most previous studies explain the effect of networks on adoption using the concept of social learning. We hope that future research will find ways to learn more about the respective roles of social learning and imitation.

4.5 Appendix

A. Additional Tables

Table A.1: Summary Statistics and Balance Table

Stats	(1) All Mean (SD)	(2) Control Mean (SD)	(3) Low Price Diff. [P-Val]	(4) High Price Diff. [P-Val]	(5) Free Diff. [P-Val]	(6) All Diff. [P-Val]
Iron Roof	0.647	0.667	0.064	0.039	-0.002	-0.028
	(0.478)	(0.472)	[0.119]	[0.250]	[0.960]	[0.322]
HH Head Female	0.303	0.308	0.012	0.033	-0.018	-0.008
	(0.460)	(0.462)	[0.768]	[0.312]	[0.578]	[0.770]
Household Size	6.690	6.789	0.172	0.070	0.189	-0.139
	(2.141)	(2.177)	[0.360]	[0.650]	[0.204]	[0.274]
Main Income is Agriculture	0.683	0.689	-0.014	-0.010	0.038	-0.009
	(0.465)	(0.463)	[0.720]	[0.766]	[0.249]	[0.757]
Business Ownership	0.294	0.331	0.015	0.106 ***	0.017	-0.052 *
	(0.456)	(0.471)	[0.708]	[0.001]	[0.613]	[0.056]
Yrs of Schooling HH Head	6.386	6.598	0.543 *	0.199	0.249	-0.292
	(3.801)	(3.890)	[0.098]	[0.478]	[0.381]	[0.209]
Number of Mobile Phones	1.398	1.426	0.043	0.027	0.049	-0.039
	(0.793)	(0.801)	[0.516]	[0.628]	[0.397]	[0.403]
Solar Lantern Ownership	0.065	0.053	-0.029	-0.014	-0.015	0.017
	(0.247)	(0.224)	[0.165]	[0.416]	[0.368]	[0.233]
Access to Electricity	0.014	0.013	-0.016	-0.000	0.002	0.002
	(0.119)	(0.111)	[0.156]	[0.978]	[0.741]	[0.724]
Observations:	1398	399	209	392	398	1398

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. A similar table is shown in Chapter 2.

Table A.2: Network Effects Controlling for HH Sampled in Village

VARIABLES	(1) Ownership	(2) Ownership	(3) Ownership	(4) Ownership
# FR knows (free)		-0.013		
		(0.011)		
# FR knows (total)		0.008*		
		(0.004)		
# in village	-0.002	-0.002	-0.001	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)
# FR knows (free) * Low Price		0.027*		
		(0.014)		
# FR knows (free) * High Price		-0.007		
		(0.011)		
Low Price	0.462***	0.447***	0.505***	0.504***
	(0.071)	(0.072)	(0.055)	(0.052)
High Price	0.270***	0.258***	0.249***	0.268***
	(0.060)	(0.052)	(0.035)	(0.037)
# in village (free)	0.004			
	(0.006)			
# in village (free) * Low Price	0.010			
	(0.007)			
# in village (free)*High Price	-0.004			
	(0.006)			
Central Person (free)			-0.048	
			(0.048)	
Central Person (free) * Low Price			0.063	
			(0.088)	
Central Person (free) * High Price			-0.012	
			(0.069)	
Central Person (free known)				-0.027
				(0.042)
Central Person (free known)* Low Price				0.084
				(0.081)
Central Person (free known) * High Price				-0.070
				(0.061)
Observations	933	930	933	933
R-squared	0.210	0.213	0.208	0.213
School FE	NO	NO	NO	NO
Controls	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES
Mean Control	0.190	0.190	0.190	0.190

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Omitted group is the control group in all tables. The outcome of interest is ownership of solar light at endline. Controlled for solar ownership at baseline as well as network size.

Table A.3: Number of Sampled HH in Villages and Number of Recipients of Free Lights

(1) Village ID	(2) Free Solar Lights	(3) Total in Village
1	9	40
2	8	28
3	5	15
4	3	5
5	13	34
6	4	28
7	0	4
8	14	43
9	2	5
10	7	29
11	0	4
12	4	18
13	3	10
14	8	27
15	7	42
16	9	17
17	2	5
18	0	1
19	0	5
20	3	9
21	1	10
22	2	5
23	1	16
24	0	1
25	2	3
26	0	4
27	0	1
28	8	18
29	3	8
30	9	31
31	22	48
32	6	15
33	7	15
34	4	17
35	10	37
36	0	5
37	6	20
38	6	33
39	3	9
40	10	46
41	0	0
42	5	18
43	0	6
44	4	14
45	12	52
46	3	17
47	3	11
48	2	4
49	3	17
50	3	9
51	12	40
52	1	8
53	1	4
54	0	3
55	0	2
56	1	8

B. Selected Survey Questions

Questions about Solar Light Price

1. What is the price for the most affordable solar lantern available?

Questions about Networks

The following questions were asked to respondents who received a voucher, as well as to those in the control group, but not to respondents who received a free solar light.

1. Do you know xxx (with the common name: yyy) or any other adult living in that household?
2. How often do you normally talk to this person?
3. Does anyone in xxx's household own a solar light?
4. How often have you spoken about solar lighting with this person?

C. Information Script about Solar Lights

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.

Chapter 5

Conclusion

5.1 Findings and contributions to the literature

Questions around the tension between economic growth and sustainability are hotly debated. Policy makers, entrepreneurs, investors, and researchers place high hopes on novel technologies that promise to increase efficiency as well as the use of renewable energies. The hope is that these technologies will create "win-win" situations, where both society at large and consumers win. The general public and future generations win due to lower emissions and pollution; consumers win because they get access to better or cheaper energy services. Yet, a number of recent impact evaluations paint a more nuanced picture. While evidence from developing economies is still very scarce, they suggest that projections often overestimate the cost-effectiveness of such technologies (Davis, Martinez & Taboada, 2018; Hanna, Duflo & Greenstone, 2016).

In Chapter 2, we provide empirical evidence that solar lights can have both considerable environmental returns as well as private returns. In that sense, they constitute an example of a "win-win" in a developing country context. The first win is that solar lights replace kerosene, and thus, reduce kerosene-related emissions. As a result, a typical household would emit 828.47 kg of CO_2 per year less, at a cost of less than US $6 per ton of CO_2, which is far below the frequently cited Social Cost of Carbon of US $50 per ton (Revesz et al., 2017; IWG, 2015). Moreover, the use of solar lights instead of kerosene improves indoor air quality and reduces symptoms related to respiratory illnesses and dry eye disease for children. These health-related findings are in line with previous studies (Furukawa, 2013; Barron & Torero, 2017; Grimm et al., 2016a), with the exception of Kudo, Shonchoy & Takahashi (2018), who finds improvements in eye health but no effects on respiratory symptoms. The second win is that having a solar light allows households to reduce their energy expenditures. Households typically save 2.7-3.4% of total monthly expenditure on average. There seems to be convergence on these figures among different studies: Grimm et al. (2016a) discovered expenditure reduction of 3% of total expenditure in Rwanda, and Kudo, Shonchoy & Takahashi (2017) find a reduction of 3.2% of total expenditure in Bangladesh.[46] In our study, purchasing a small solar light pays off within the first 14 months, even when considering the high local interest rate of 7.5% per month. That said, a solar light does require an up-front payment corresponding to 12% of average monthly expenditures and there is a legitimate risk of product failure. After seven months, 7.8% of solar lights stopped working. According to our estimates, the cost of the larger solar light, which can be used to charge a mobile phone, could not be recouped within the first two years.

An important pre-condition for any technology to make a difference is that beneficiaries use it, which can be challenging to confirm with traditional survey methods since respondents might overreport use, thinking this is what is expected from them (social desirability bias) (Wilson et al., 2016; Thomas et al., 2013). Chapter 3 takes a closer look at whether and how households used the solar lights based on data from 220 sensors. Furthermore, we compare sensor data with survey data and test different hypotheses about systemic biases in survey data that have been put forward in the literature. It is important to learn about these biases as they cast doubt on the validity of survey answers and thus, a large part of social science research. First, we test whether we find evidence for social desirability bias, whereby respondents systematically overreport use. We do not find evidence of this effect on average, however, we do find that households that hardly use the solar light tend to overreport use (while those who use it a lot tend to underreport). Second, we test whether households with frequent visits from surveyors use the solar lights more. While use increased initially, it had no long-term effects.

Demand for solar lights is highly sensitive to price changes. While 68.8% of those who could purchase a solar light at 400 KES (US $4) bought one, take-up decreased to 37.4% when the price increased to 700 KES (US $7). Take-up was only at 28.9% when the solar light was sold at 900 KES (US $9). Overall, willingness-to-pay was higher in our study compared with previous studies, however, a direct comparison might not make sense since other studies did not provide vouchers, but instead played auction games (Grimm et al., 2016b; Niccolò et al., unpublished; Yoon, Urpelainen & Kandlikar, 2016). In Chapter 4, we discuss direct and indirect effects of subsidies on solar light take-up and use in more detail. We test whether price affects use as the sunk cost effect or selection effect would predict (Ashraf, Berry & Shapiro, 2010; Cohen & Dupas, 2010;

[46] This is only significant at the 10% level. However, it is only 1.6% of total expenditure, which is not significant at the 10% when they do control for baseline.

Dupas, 2014; Thaler, 1980). We find no difference between households that paid the full market price for the solar light and those who received one for free or at a subsidized price. Finally, we find that social interactions with adopters might affect purchasing decisions, whereby the price sensitivity of demand tends to increase. While we think that more research would be needed to confirm this finding, it suggests that the effectiveness of subsidies would increase over time. Taken together, these findings indicate that further price reductions are likely to increase product take-up and use and that they are needed to boost adoption above 50%. Increased take-up would then lead to a reduction in kerosene use, which has health and environmental benefits. According to our estimates, the cost per ton of CO_2 equivalent averted would be lower than the Social Cost of Carbon. In addition, solar lights provide access to a basic form of modern energy, which is an important policy goal for many governments as well as the United Nations. Finally, at least in the short run, off-grid solar solutions might be more cost-effective than grid extension in some contexts (Lee et al 2016b).

Solar lights also have their limitations and a number of important questions remain unanswered. Access to electricity for other purposes besides lighting is also limited and these small solar lights do not allow households to power larger appliances, like a television. Therefore, they will not provide enough energy for rising living standards. In terms of indoor air pollution, cookstoves are a bigger culprit than kerosene lights. To achieve substantial health gains, reduced harmful emissions from cookstoves would have to be addressed too, which seems to be a rather challenging endeavor (WHO, 2016). In addition, the total contribution of kerosene lighting to global warming is very limited. Recent estimates suggest that total emissions from kerosene used for lighting has the same warming effect as 4.5% of the total United States' CO_2 emissions (Lam et al., 2012a; Jacobson et al., 2013). We also did not find any effects on children's test scores and this seems to be the same in other studies who looked at the issue (Furukawa, 2013; Kudo, Shonchoy & Takahashi, 2017). This finding stands in contrast to what a number of distributors and producers of solar lights claim in their advertising. Some companies even use head teachers' and teachers' time to sell and promote solar lights (Solar Aid, 2013), which may not be justified given our results.

Recent developments in the off-grid solar field aim to address some of these limitations. Pay-As-You-Go systems are increasingly used that do not require large, up-front payments and allow consumers to pay for solar products as they use them. Moreover, modular systems, which allow costumers to increase their off-grid solar capacity as living standards rise, are gaining traction (GOOGLA, 2018). Earlier this year, a company providing modular products signed a deal with the government of DRC to provide off-grid solar access to 2.5 million people (African Review, 2018). Another important caveat is that the health and environmental effects discussed in this thesis rely on the fact that, in our study setting, solar lighting replaced kerosene, however, battery-powered torches also increasingly replace kerosene, at least in places where kerosene is not subsidized (Bensch, Peters & Sievert, 2017). In cases where kerosene is hardly used the impacts would look quite different. Finally, one would have to find a solution for maintenance and recycling of old solar lights, especially their batteries. Otherwise, solar lights might create new environmental challenges.

5.2 Potential pathways for future research

Generally, we hope that more evaluations will study the impact and cost-effectiveness of programs that aim to reduce CO_2 emissions in both developed and developing countries. There are very large differences in the cost-effectiveness of existing programs and we saw repeatedly that lab tests and engineering projections cannot replace empirical studies in a real-world setting. In developing economies, impact evaluations of different policy options seem particularly important as governments are more resource constrained and investing in ineffective policies has higher opportunity costs. Moreover, this is where energy demand and greenhouse gas emissions are projected to grow most significantly in the coming years.

Sensors could be useful for conducting these evaluations because they provide more objective and less intrusive ways of measuring technology adoption. Moreover, comparing sensor data with different types of survey questions has additional benefits: It can help us learn more about how to optimally design survey tools and reduce biases in survey data. Building on our study, as well as on findings from Wilson et al. (2016) and Thomas et al. (2013), further studies should look at how over- and underreporting plays out at different levels of use intensity and whether and how this can be explained by social desirability bias. Understanding the conditions under which this bias is particularly prevalent can help researchers decide when it is most necessary to use sensors instead of or in addition to self-reported answers. Researchers can even go a step further and learn more about how the set up of a study matters beyond survey tools, which is very hard to study otherwise. Such research set-up issues include how the research is framed to respondents and surveyors, characteristics of the surveyor, the extent to which respondents associate the research team with the product or the intervention, and so on. This type of measurement study could either reassure researchers about current measurement methods or propose ways to improve them.

For off-gird solar, in particular, we hope that future research will assess their impact in populations where most people use battery-powered torches and/or are connected to the grid and use them as a battery back-up, as it is likely that this will be the counter-factual in many places in the future. Moreover, we hope that researchers will assess the impacts of new approaches, including Pay-As-You-Go and modular systems, which are getting increased attention in the policy world. In terms of technology adoption, it would be interesting to understand how Pay-As-You-Go and modular systems affect willingness-to-pay and to what extent they succeed in boosting adoption at a large scale. With regard to health impacts, we hope that future research will assess how indoor air pollution from lighting interacts with pollution from cooking and what combination of interventions can achieve the most substantial health gains. Finally, it would also be important to design and test solutions for recycling and maintenance of solar systems. Electronic waste seems to be becoming an increasingly large problem in developing countries as living standards rise and, if not addressed properly, might create additional environmental challenges.

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