Environment for Development

Discussion Paper Series June 2015 ■ EfD DP 15-14

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Abstract

Although Kenya enjoys a high and widespread daily solar insolation, and despite enactment of policies to promote adoption of renewable energy technologies, not many households have picked up solar technologies. The objective of this study is to find out the incidence and predictors of actual up-take of solar technology as well as households' desire to switch to solar in light of their perception of its cost advantage. We find that the main predictors of the odds for installation of solar panels include household prosperity, for which total household expenditure is an indicator. Formal employment by the head of household is also crucial in increasing the odds for both actual adoption and an interest in switching to solar energy. Our results suggest that initial solar adoption requires a higher socioeconomic threshold than subsequent interest in switching after the benefits of solar energy become evident. More generally, the results suggest that anti-poverty policies, including those that promote expansion of formal employment opportunities, will increase the use of cleaner and more convenient forms of energy, such as solar energy.

Key Words: solar technology, adoption, switching, energy, Kenya

JEL Codes: Q40, Q42, Q48, Q50, Q58

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John Mutua and Peter Kimuyu*

1. Introduction

Solar technologies made their debut in Kenya in the early 1980s following earlier oil price escalations. Solar power avoids the undesirable environmental consequences associated with fossil and nuclear fuels. Large hydro-power schemes are also often problematic, and the remaining hydro-potential in Kenya is small scale and limited in quantum.[1] The majority of people living in Sub-Saharan Africa do not have access to electricity (Jack and Suri 2013). Traditional power companies often find it too costly to bring electricity to rural and suburban areas.

However, Kenya is lucky because it receives 4-6 WH/M^2 of daily solar insolation, spread all across the country.[2] Yet, solar uptake has been low. This paper explores the predictors of households adopting and planning to adopt solar technology.

Despite the high solar insolation in Kenya, recent studies show that adoption of this technology was 1% (KIPPRA 2010). The situation is, however, changing due to initiatives such as the removal of Value Added Tax (VAT) for solar panels and increased adoption pushed by the private sector. The M-KOPA program, which is spearheaded by Safaricom, the leading mobile provider in Kenya, has connected more than 150,000 homes in Kenya, Tanzania and Uganda to solar power since its commercial launch in October 2012, and is said to add over 500 new homes each day (M-KOPA Solar & Inter Media 2015).The majority of these households are in Kenya.

Photovoltaic technology has a long history, with photoelectric effects having been discovered about 1839 (Acker and Kammen 1994). However, the spread of solar technology was initially undermined by a combination of very low light-to-electricity efficiencies and high costs,

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[1]Large hydro projects can precipitate socioeconomic disruptions, including displacement of populations. They are also prone to early exhaustion because such schemes are on the front end of what are seen as low-cost sources of electricity.

[2]There are also many locations in the country with potential for wind energy (Kimuyu et al. 2011).

so that such technology was not commercially viable for a long time. Efficiencies were as low as 1% over the first 100 years, until about 1950, when crystalline silicon solar technologies made their debut. In any case, these parameters improved significantly over time, so that, by 1990, commercially available PV modules had achieved 14% efficiency. About the same time, efficiencies as high as 25% were being reported from research laboratories.

Although attempts have been made to popularize solar and wind technologies over the years, and despite initial significant achievements during the 1980s, and more recently under the M-KOPA program, progress in the adoption of these technologies is still modest. An oil price shock in 1973-74 helped open up the market for photovoltaic (PV) cells because it forced governments to start looking for reliable and fiscally predictable alternatives to oil. At the time, prices of such cells were very high. A 40 peak watts panel in the 1970s cost more than US$ 1200, far out of the reach of most Kenyan households (Acker and Kammen 1994). Furthermore, all the panels had to be imported, as there was no local fabrication. By the 1980s, PV prices were on the decline. Donor agencies operating in Kenya made solar panels the technology of choice in rural locations where electricity was required for such activities as vaccine refrigeration, school lighting and water pumping. This period was also marked by a very intensive search for renewable technologies. In response to donor needs, large international companies dealing with solar panels opened regional offices in Nairobi. A few Kenyan firms making solar panels also made their debut, specializing in large-scale solar systems and avoiding the household sector. This market development saw the prices per peak watt decline from US$ 40 in 1970 to less than US$ 5 in 1993. That trend has continued over the years.

The main policy question that this research seeks to address is why these renewable energy technologies have not taken root and what else should be done to spread their use in Kenya. Why has the adoption of solar technologies been slow and what constraints deter adoption?

More specifically, this paper seeks to find out the incidence of use as well as planned use of solar energy by Kenyan households, establish social or economic factors influencing these choices, and suggest policy proposals for increasing the use of solar energy in Kenya. These objectives are pursued by applying discrete choice models to explore predictors of installation of solar panels and factors that determine the odds that households choose solar energy, rather than other sources of electric energy, as their main source of energy for lighting electricity. This methodology is applied to household survey datasets and confirms the importance of the socioeconomic status of households and household heads' attributes in driving solar energy related decisions. This is true for existing adoption of solar technology as well as planned switch to solar energy. We also find that the household income threshold at which households adopt solar energy is greater than that for planned switch to solar energy.

The rest of the paper is organized as follows: in section two, we review the literature on adoption of technology, beginning with a discussion about the theoretical shape of technological diffusion depending on the relative compositions of innovators and imitators, and proceeding to review the more empirical literature, with a focus on literature specific to Kenya. Section three presents the study's methodological approach and includes a discussion of the data and the empirical models to which such data are applied. This section is then followed by a summary of what the data suggests about the domestic energy economy in Kenya. The results are presented in section five, while the summary follows in the sixth and last section.

2. Theory and Literature

Some background about technology adoption in general can help explain solar adoption in Kenya. Two observed regularities about adoption of new technology are that such adoption is not instantaneous, because households pick up technological breakthroughs only slowly, and that, following initial adoption, diffusion across households tends to take an S-shape, with some households adopting early while others take their time (Hoppe 2002). Delays in the absorption of new technology are attributed to interactions between supply-side and demand-side forces, such as expected reductions in the costs of producing the new technology. There are likely to be learning-by-doing effects that tend to reduce the cost of production. Expectations related to such effects reduce the incentive to immediately switch to new technologies and are a barrier to technological adoption (Jovanovic and Lach 1989, also mentioned in Hoppe 2002). Vintage-specific skills may be important in effective adoption of new technology, further explaining why uptake of such technology tends to be slow.

The benefits of technological adoption critically depend on the mass of other adopters, so that households have an incentive to delay adoption until more eager ones have already adopted (Farrel and Saloner 1985, also mentioned in Hoppe 2002). This is related to a further reason for delaying adoption: the presence of uncertainty. Expected post-adoption benefits are based on a belief about the benefits of adoption. For this reason, a household will delay the adoption of new technology to a time when the "current estimate of the likelihood that the innovation is profitable exceeds the reservation level and if it is not more profitable to wait for more information or arrival of better technology." In other words, uncertainty about the value of the new technology reduces or increases a household's adoption incentive, depending on whether beliefs are pessimistic or optimistic. The possibility of resolving uncertainty over time by collecting information about the unknown value or the arrival of better technology unambiguously introduces an incentive to delay adoption. Uncertainty may also be reduced by observing the experience of other adopters, which generates an incentive to wait until other households move first (Hoppe 2002 p.59).

Even where there is certainty about the value of currently available technologies, uncertainty may relate to the arrival of a better version of such technology. The announcement of new discoveries often delays the adoption of new technology. Although households can buy information about anticipated technological improvements, such households are likely to delay adoption of available technology if the anticipated improvements are large (Weiss 1994). For example, a consumer may pay to attend a solar expedition to check on the available technology but may delay the actual purchase of the technology if they perceive that more improvements are being done to make it more efficient, improve quality and reduce the price. Until the technology is sufficiently advanced, there are further incentives for adoption delays when there are anticipated improvements.[3]

Adoption of any new technology is like a timing or waiting game, in which the experiences of an adopting agent can be observed by other agents, with the structure of the game being of a nature that allows the experience of early adopters to reveal to other agents the exact nature and quality of the new technology. In that case, each household prefers others to make the first move. In this waiting game, slow technology adoption can result from informational externalities, while positive probabilities of never adopting raise possibilities of an infinite delay. The adoption by one household, while not fully revealing the true nature of the technology, is bound to provide a signal to other households. Such a signal is useful in updating prior beliefs about the technology. This makes the waiting game sequential in the sense that, when one household adopts, one waiting contest ends and others revise their beliefs as they participate in the subsequent waiting contest (Kapur 1995).

The rate of technological diffusion also depends on the population of potential adopters (Roset and Canals 2011). Such a population can be broken into two subgroups based on the inclination to adopt new technologies. One group consists of innovators or those more likely to procure the technology on the basis of factors external to the population, such as product communications and advertising, while another consists of imitators, whose adoption is a

[3] The literature argues that this probably explains lags between development of new technology and its adoption in the US steel industry (Doraszelski 2000).

response to external factors as well as interactions with innovators or previous adopters. There are also possibilities of dual markets that derive from informational cascades that arise when consumers make their decisions on the basis of observed behavior of a few rather than individual analysis of the benefits of available alternatives. In other words, while some agents acquire new technology based on its merit, others procure the technology out of imitation of the earlier group, increasing sales. Growth in sales encourages new adopters to a level that would be impossible through the route of individual assessment of the benefits of the new technology by each agent. In the early stages of the adoption process, visionaries and tech-savvy enthusiasts dominate those adopting. These simply use product specifications and assessment of the benefits of the new technology. Subsequent adopters take other things into consideration. Nevertheless, the speed of adoption is determined by feedback between innovators and imitators in that kind of an environment.

A major constraint to the adoption of renewable energy technologies (Bazart 2003 and Ilie 2007) is that the initial capital outlay for these technologies tends to be high. Around the world, attempts to adopt new or improved technologies often fail because they focus on the "hardware" and ignore the complex mix of interconnected social, institutional, economic and policy issues that can limit success (IIED 2013).

Specific factors that undermined the spread of solar technology in the Kenyan market in the recent past include a changed political climate following the collapse of communism, which eroded Kenya's geopolitical strategic position, precipitating a waning of donor interest and programs (Acker and Kammen 1994). Others include renewed escalation of the prices of solar technology due to foreign exchange fluctuations, general inflation and import tariffs. For these reasons, only the affluent could afford PV panels. However, empirical evidence on adoption of renewable energy technology (RET) in Kenya leads to the conclusion that such technology could meet a significant proportion of the country's energy demand (Karekezi and Kithyoma 2003).

Using the option value framework to examine decisions by households to invest in solar PV, and quantifying the option value multiplier and adoption rate over time for solar PV investments, Bauner and Crago (2014) established that the option value multiplier is 1.8, so that the net present value of benefits from solar PV needs to be almost double the investment cost for investment to occur. Simulated adoption rates show that the adoption rate under the option value decision rule is significantly lower than that following a decision rule based on NPV, and is more consistent with the observed adoption rate of solar PV. Such simulations further show that, without tax credits and rebates, the median time to adoption increases by 110% compared to the baseline with such credits and rebates.

Governments can encourage alternative state and non-state entities to venture into power generation through a "feed-in tariffs" mechanism for every registered renewable energy power plant (Dusko and Marinela 2010). Kenya is already exploring this approach, which has been successfully applied elsewhere. Masa (2010), assessing two models of solar home systems (SHS) on a selection of variables, argues that the success of a particular technology hinges on the projects' conformity with the institutional development in the country. Institutions are therefore important. Furthermore, the success of a technology transfer depends on the accessibility of the technology to the target users.

An interdisciplinary approach to exploring the forces underpinning the adoption and non-adoption of solar PV in rural Ghana revealed that Ghana has abundant renewable energy resources, especially solar radiation (Bawakyillenuo 2007). Significantly, adoption and non-adoption prospects for solar PV in rural Ghana and the sustainability of installed solar PV systems, as well as the disparate levels of solar PV dissemination in Ghana, Kenya and Zimbabwe, are predicated on multi-dimensional circumstances. This is in contrast with other literature that emphasizes cost as the sole determining factor of the non-adoption of solar PV in the developing world.

Although capacity planners in developing countries frequently use screening curves and other system-independent metrics such as levelized cost of energy to guide investment decisions, this can lead to spurious conclusions when evaluating intermittent power sources such as solar and wind (Rose et al. 2014). A system-level model to evaluate the potential of using grid-connected solar photovoltaic in combination with existing reservoir hydro-power to displace diesel in Kenya shows that the value of high penetrations of solar in 2012 exceeded their potential investment cost. This research also shows that the investment value of solar is particularly high if planned investments in low-cost geothermal, imported hydro, and wind power are delayed.

Other studies (Lay et al. 2013) have confirmed the existence of an energy ladder in Kenya, with poor households using traditional fuels, and have shown that incomes play an important role in switching to transitional and more modern fuels. In assessing market conditions that influence the adoption and maintenance of solar systems in developing countries using an economic cost method, Chapman and Erickson (1995) found that cost reduction is necessary before PV systems can be broadly competitive.

To summarize, this overview of solar adoption literature seems to suggest, at the theoretical level, that adoption of solar technology may be delayed by the mere existence of a large proportion of late adopters, expectations about improvements in solar technology and reduction in costs, and uncertainty about the real benefits of such adoption. A majority of studies have used screening curves and other system-independent metrics, economic cost models, system-level models, interdisciplinary approaches and option value frameworks. While some of these models are suitable for analyzing adoption of technology, they are weak in analyzing socioeconomic factors that drive adoption. Discrete models of the Probit and Logit type applied on household level socioeconomic data are suitable for analyzing the adoption of solar technology. This paper uses such models to bridge the literature.

3. Methods

This paper makes use of the Kenya National Energy Survey (KNES) data of 2009, collected by the Kenya Institute for Public Policy Research and Analysis (KIPPRA) on behalf of the Ministry of Energy and the Energy Regulatory Commission. The survey was implemented between May and June 2009 in the then eight provinces of Kenya and administered at the district administrative levels.[4] It was based on the National Sample Survey and Evaluation Program (NASSEP) IV sampling frame. After the 1999 Population Census, the Kenya National Bureau of Statistics (KNBS) established a frame of 1,800 clusters, each with 100 households on average, with the aim of conducting socioeconomic surveys. Of the 1,800 clusters, 1,260 were rural while the rest were urban. The KNES undertook a survey of a 20% sub-sample of the clusters, resulting in 108 urban clusters and 252 rural clusters.

From that sample, 1,080 urban households and 2,520 rural households were targeted. The survey was well responded to and managed to interview 3,665, above the 3,590 target. The survey instrument had six sub-sections/modules, which included a profile of the energy consumers, energy choices and uses, energy costs and expenditures, customer satisfaction, willingness to pay, household socioeconomic characteristics and a demographic profile of consumers. Section two of the questionnaire was devoted to gathering information on the main sources of cooking and lighting fuels, and elicited detailed information on the utilization of firewood, grass, paraffin, electricity, solar, liquefied petroleum gas (LPG), charcoal, biomass, biogas and other forms of energy. Section three of the questionnaire focused on energy costs and expenditures and included issues of energy efficiency and switch options.

Our analysis is founded on utility theory, which permits use of discrete choice models, through which adoption of renewable energy technologies can be investigated (Heltberg 2005). It

[4]The districts have since been converted to counties.

is assumed in the models that households are unitary rather than collective, that the household head acts in the best interest of other members of the household, and therefore that the personal attributes of the household head weigh heavily in the choice to either adopt or not adopt solar technology. Discrete choice models are the most suitable for this study because the dependent variable, in the context of domestic uses, presents itself as a categorical set of n-fold alternative choices such as solar-based technology, biogas technology and others, including electricity, wind, charcoal or biomass (Madalla 1984). In a sense, a household has to choose solar energy against other forms of energy used for different domestic purposes. Of specific interest to this study are lighting energy choices. The choice of a particular form of domestic energy is expected to be driven by two sets of attributes, namely those associated with the households and those associated with the specific form of energy.

To explore the odds for choosing solar energy rather than other forms of electrical energy for lighting purposes, we propose to use a simple logistic model to explore household choices related to installation of solar panels and planned switch to solar energy. A logistic model is used because the dependent variables, namely installation of solar panels and planned switch to solar energy, take only two values, 1 for installation or planned switch, and 0 otherwise, whatever the combination of independent variables. A binary response variable y, such as installation of solar panels, has two categories,[5] and the same categories are used the anticipated switch to solar energy. The mean of these 0 and 1 outcomes is the same as the proportion of outcomes that equal 1. The response models for binary responses such as these describe the proportions of the population. Furthermore, the population’s proportion of success, i.e., the proportion for which an outcome of 1 is observed, represents the probability P(y=1) for any case which is randomly selected. However, this probability is bound to vary with the specific values of the explanatory variables associated with the case. Models that use binary data such as install/not install or switch/not switch assume that the dependent variables share binomial distribution, and are restricted cases of general linear models.

The logistic regression model of binary responses with a single explanatory variable is simply

$$Pr[y = 1] = \alpha + \beta x$$

[5] The generic terms for these two outcomes are success on the one hand and failure on the other.

with x as the only dependent variable. This is referred to as the linear probability model. The corresponding logistic relationship is described by the formula

$$\log\left[\frac{Pr(y=1)}{1-Pr(y=1}\right] = \alpha + \beta x$$

When the explanatory variables are many, a multiple logistic model is generated, taking the form

$$logit[Pr(y=1)] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$$

so that the probability itself is represented by

$$Pr(y=1) = \frac{e^{\alpha+\beta_1 x_1+\beta_2 x_2+\cdots\beta_k x_k}}{1+e^{\alpha+\beta_1 x_1+\beta_2 x_2+\cdots\beta_k x_k}}$$

Obtaining the exponentials of the beta parameters gives the multiplicative effect of the predictors on the odds for the specific outcome, other variables kept under control. The further away a β_i falls from 0, the stronger the effect of the predictor variable x_i.

4. Household Fuel Economy in Kenya

There are two main domestic uses of energy, namely cooking and lighting, according to the KIHBS survey, which was carried out in 2005/6. The frequencies of domestic use of different forms of energy are summarized in Table 1. This table reveals that biomass (firewood, charcoal and grass) accounts for more than three-quarters of the total national energy used for cooking in Kenya. This contribution is higher in rural Kenya, where biomass accounts for more than 90% of energy used for cooking; the corresponding figure for urban consumption is slightly more than 50%. Unpacking biomass as a cooking energy shows that, whereas firewood accounts for about 90% of total biomass used for cooking in rural Kenya, it accounts for only 18% percent in urban areas, where charcoal dominates cooking energy. Other than biomass, paraffin is the second most important source of cooking energy, accounting for 11% nationally but only about 2% in rural Kenya. In urban areas, paraffin accounts for more than a quarter of all the energy used by households for cooking.

Table 1: Main Sources of Cooking Fuels (Figures in Percentages)

	Location		
	Rural	Urban	National
Firewood - Collected	90.34 *78.39*	17.69 11.55	62.63 52.90
Charcoal	6.33	39.94	19.15
LPG	0.55	11.48	4.72
Paraffin	1.82	26.86	11.37
Electricity	0.12	2.08	0.87
Other (grass, biomass residue, biogas, other)	0.84	1.95	1.27
Sample size	43,957	27,106	71,065

Source: KNBS, 2007

Turning to domestic lighting, paraffin is nationally the most important source of energy for that purpose, accounting for nearly three-quarters of lighting energy (Table 2). Paraffin contributes an even higher percentage of lighting fuels in rural Kenya, where its contribution is upwards of 85%. In urban Kenya, paraffin contributes slightly more than one-half of lighting energy. Electricity is the second most important source of lighting energy, with a national contribution of about 18%. It is used for lighting in urban Kenya, where it meets 42% of households' lighting needs. In rural areas, it accounts for about 2.5% of the lighting energy. Here, it is followed very closely by solar energy, which accounts for about 2% of the lighting energy. The national figure for the contribution of solar energy in household lighting is about 1.6%.

Table 2: Main Sources of Lighting Fuels (Figures in Percentages)

	Location		
	Rural	Urban	National
Firewood - Collected	*6.94* 6.69	*1.22* 1.05	4.76 4.54
Torch	2.40	0.38	1.67
LPG	0.17	0.30	0.22
Paraffin	85.42	54.25	73.53
Electricity	2.69	42.22	17.81
Solar	2.10	0.67	1.56
Other (grass, candle sticks, other)	0.27	0.87	0.49
Sample size	43,957	27,106	71,065

Source: KNBS, 2007

With regard to solar energy use in Kenya by national, urban and rural areas, the National Energy Survey 2009 indicates that solar recorded 3% of the national sample while urban and rural areas recorded 0.3% and 2.7%, respectively. The widely used fuels for lighting were kerosene (80%), followed by charcoal (60%), fuel wood (55%), electricity (29%) and LPG (21%), in that order (Table 3). The usage of fuel wood, charcoal and kerosene in rural areas is higher, compared to urban areas. However, the use of LPG and electricity in rural areas is lower than that in urban areas. While lower prevalence of electricity use in rural areas can be attributed to lack of connectivity, lower LPG use can be attributed to inadequate access and information (KIPPRA 2010).

Table 3: Fuel Type by Urban and Rural Areas (Percentage)

Fuel type	National	Urban	Rural
Material Residue	7.4	0.4	7.0
Fuel wood	55.0	3.8	51.0
Charcoal	60.0	24.0	36.0
Kerosene	80.0	22.5	58.0
LPG	21.0	14.0	6.3
Biogas	0.2	0.0	0.2
Electricity	28.9	37.0	12.0
Solar	3.0	0.3	2.7
Lubricants	0.8	0.4	0.4
Wind	0.1	0.0	0.1
Other petroleum product	1.8	1.0	0.7
Others (candles , batteries)	2.1	0.7	1.4

Source: National Energy Survey 2009.

In the analysis, we also perform some cross-tabulations of the switch options between the perceived level of cleanliness and the perceived level of costs. The results are presented in Table 4 below. From the analysis, it is evident that 83.3% of respondents perceived that solar is both clean and cheap, while 61.3% felt that it was affordable and very clean. However, 74.9% felt that, although solar is clean, it is very expensive. None of the respondents indicated that they would not switch to solar because it was less clean and cheaper; in other words, all households perceive solar as clean. From these results, it is evident that very few or none of the respondents felt solar, as a switch option, was less clean or contributed to indoor pollution, even when switching because of the costs of the service was an impediment. This is an indication that that the majority of households would switch to solar because it is perceived as clean, if cost was not an impediment to switching.

Table 4: Level of Perceived Cost Vs Perceived Cleanliness of Solar

Perceptions about level of cleanliness of solar (%)	Perceptions about the costs of solar (%)				
	Very cheap	Affordable	Just right	Expensive	Very expensive
Very clean	83.33	61.31	60.84	61.93	74.90
Clean	12.22	32.48	25.90	31.28	18.42
Undecided	2.22	5.47	10.84	5.37	5.87
Less clean	0.00	0.73	1.81	0.95	0.61
Associated with indoor pollution	2.22	0.00	0.60	0.47	0.20
Total	100	100	100	100	100

Source: National Energy Survey 2009.

5. Empirical Results

5.1 Descriptive Statistics

This sub-section presents descriptive statistics of the variables in the analysis (Table 5). From the data, about 3% of households in the sample use solar. These are mainly in the rural areas. On the other hand, about 29% use electricity supplied by Kenya Power and Lighting Company Limited, which is the sole distributor of grid electricity in the country. Kenya has a single buyer model. About 66% of the households studied are in the rural areas, meaning that only 34% are urban-based. The mean log of total household expenditure[6], which is used as a proxy for socioeconomic status, is 9.33. This means that the average monthly household expenditure in the sample is Ksh. 11,271 or US$ 132 given the exchange rate at that time. From

[6]Household expenditures are used more than direct income because they are easier to remember. Respondents tend to remember what amounts they spent and for what purpose, provided the reference period is not too long. Another strong argument in favor of using expenditure data is that such data represent actual and not potential (as is the case with income) consumption, thus providing a more accurate measure of economic welfare (Kumar 1989).

the sample, about 47% of the respondents were in formal employment, meaning that 53% were in the informal sector. The average household size was five (5), which is consistent with the 2009 national population census. The number of households headed by females in the sample was 61%, signifying the increasing role of single mothers and widows in running households. Household heads with primary education accounted for 29%, while 52.5% had secondary and post-secondary education. Only 18.5% had no education at all. These results suggest a high level of literacy in the Kenyan population. With regard to awareness of regulations, only 15% and 5% were aware of Energy Regulatory Commission (ERC) and general energy regulations and National Environment Management Authority (NEMA) regulations, respectively.

Table 5: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Solar	3665	0.030	0.171	0.00	1.00
Battery and candle	3665	0.021	0.143	0.00	1.00
Electricity/KPLC Supply	3665	0.368	0.482	0.00	1.00
Rural	3665	0.659	0.474	0.00	1.00
Log of total expenditure per month	3649	9.326	0.792	5.70	12.78
Formal employment	3665	0.466	0.499	0.00	1.00
Household size	3665	5.145	3.011	1.00	50.00
Log of price of electricity	3665	2.753	0.602	0.11	10.31
Female dummy	3665	0.613	0.487	0.00	1.00
Primary education dummy	3665	0.290	0.454	0.00	1.00
Secondary +post-secondary education dummy	3665	0.525	0.499	0.00	1.00
Awareness of regulations	3665	0.151	0.359	0.00	1.00
Awareness of NEMA Regulations	3665	0.051	0.220	0.00	1.00
Solar switch cost options	3665	0.144	0.532	0.00	1.00

5.2 Quantitative Analysis Results

5.2.1 The Odds for Installing Solar Panels

The results of the discrete choice models reveal that personal attributes of the household head are important predictors of the odds for installation of solar panels (Table 6). The fact that a household head has secondary education counts for installation of solar panels for the national sample but not when the sample is split between urban and rural. However, this is not the case for those households whose head has a primary education. Households headed by persons in formal employment are more likely to adopt solar technologies compared to those in informal sectors, suggesting that the high levels of unemployment evident in Kenya are a major constraint to the adoption of solar energy.

There is also co-movement between household size and the likelihood for installation of solar panels, so that larger households are more likely than smaller ones to have such installations. This is especially the case for the full sample, as well as for the urban sub-sample. Other socioeconomic variables also predict the odds for such installation. Total non-food household expenditure and solar installations move in opposite directions nationally. In other words, households that are relatively well off are more likely to install solar panels. The coefficient for the rural sample has a positive sign, suggesting a positive impact on solar installation, i.e., households in rural areas are more likely to adopt solar technologies compared to the urban-based ones. This picks up the effect of poorer access to the national grid in remote rural areas of Kenya. Evidently, solar energy in Kenya is largely a rural phenomenon.

With regard to the regulatory environment, awareness of regulations by ERC and related agencies has a positive impact on solar technology adoption. However, awareness of regulations by NEMA has no implications for adoption of solar technologies nationally but seems to discourage solar adoption in rural Kenya.

Table 6: Estimated Results for the Odds for Installing Solar Panels

Variables	Rural		Urban		National	
	logit estimates	marginal estimates	logit estimates	marginal estimates	logit estimates	marginal estimates
Solar	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx
Rural					1.911 (6.03)*	0.0313 (7.2)*
Log of total expenditure	0.691 (4.2)*	0.019 (4.36)*	0.171 (0.44)	0.001 (0.44)	0.595 (3.97)*	0.011 (4.04)*
Formal employment	0.666 (2.98)*	0.020 (2.70)*	-0.434 (-0.70)	-0.004 (-0.65)	0.534 (2.52)*	0.011 (2.42)*
Household size	0.032 (1.14)	0.001 (1.13)	0.108 (1.43)	0.001 (1.45)	0.036 (1.37)	0.001 (1.36)
Log of electricity price	0.059 (0.33)	0.002 (0.33)	-0.297 (-0.72)	-0.002 (-0.74)	0.009 (0.05)	0.001 (0.05)
Female	0.044 (0.2)	0.001 (0.21)	-0.516 (-0.88)	-0.005 (-0.83)	-0.015 (-0.07)	-0.0002 (-0.07)
Primary education	-0.500(-1.27)	-0.013 (-1.35)	0.546 (0.51)	0.006 (0.43)	-0.346 (-0.95)	-0.006(-1.01)
Post-secondary education	0.490 (1.61)	0.014 (1.59)	0.671 (0.81)	0.006(0.86)	0.533 (1.88)*	0.0102 (1.87)*
Awareness of regulations	0.016 (0.05)	0.0004 (0.05)	0.087 (0.11)	0.0007 (0.11)	0.031 (0.11)	0.0005(0.11)
Awareness of NEMA regulations	-1.235 (-.65)	-0.021 (-2.85)*	-5.909 (-.42)	0.001 (0.914)	-1.34 (-1.81)*	-0.015 (-3.26)*
Constant	-10.467 (-6.31)*				-11.289 (-7.03)	

Notes: (1) Number of observations: National (3,649), Rural (2,404) and Urban (1,172); (2) Figures in parentheses are absolute z scores/ratios; (3) An asterisk shows significance at least at the 10 percent level.

5.2.2 Planned Switch to Solar

The KNES (2009) data sets include responses to questions about whether households plan to shift to specific forms of energy for lighting on account of perceived cost and cleanliness advantages. Included in the basket of lighting energy options was solar energy.[7] For this level of

[7]The question in the survey instrument read as follows: 'For each of the forms of energy consumed, are you willing to change from the current energy consumed to an alternative? If 'yes', to which alternative would you prefer to switch? What is the main reason for desiring to shift to the fuel indicated?'

analysis, we use the information so generated to explore the odds for switching to solar technologies due to perceived lower cost.[8] The solar switching model was estimated for the national, rural and urban sample.

The analysis reveals that personal attributes of the household head, such as being in formal employment and having post-secondary education, are important predictors of the odds for being interested in switching to solar energy, just as was the case with actual solar adoption (Table 7). A household whose head is engaged in formal employment is more likely to want to switch to solar due to its perceived low cost. Similarly, households headed by people with post-secondary education are more likely to want to switch to solar due to perceived cost relative to those headed by persons who have not been to school. Households that are larger are also more likely to want to switch to solar energy. The finding that electricity prices dampen the odds for wanting to switch to solar is inexplicable.

[8]Initially, we explored the desire to switch due to cleanliness as well as cost. The former, however, wasnot significant and was therefore not explored further.

Table 7: Estimated Result for the Odds for Switching to Solar Energy

Variables	Rural		Urban		National	
	Logit estimates	Marginal estimates	Logit estimates	Marginal estimates	Logit estimates	Marginal estimates
	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx
Rural					0.104(0.94)	0.012(0.95)
Log of total expenditure	0.221 (2.41)*	0.026(2.42)*	0.166 (1.39)	0.021 (1.40)	0.193 (2.71)*	0.023 (2.72)*
Formal employment	0.438 (3.47)*	0.053 (3.33)*	0.382 (1.98)*	0.045 (2.10)*	0.424 (4.03)*	0.052 (4.01)*
Household size	0.042 (2.31)*	0.005 (2.31)*	-0.039 (-1.05)	-0.005 (-1.05)	0.023 (1.45)	0.003 (1.46)
Log of electricity price	0.023 (0.17)	0.003 (0.17)	-0.317 (-2.76)*	-0.040 (-2.81)*	-0.219 (-2.49)*	-0.026 (-2.50)*
Female	0.045 (0.37)	0.005 (0.37)	0.063 (0.38)	0.008 (0.38)	0.036 (0.37)	0.004 (0.37)
Primary education	0.300 (1.44)	0.036 (1.44)	0.121 (0.42)	0.016 (0.41)	0.175 (1.1)	0.022 (1.07)
Post-secondary education	0.573 (2.98)	0.067 (2.97)*	0.102 (0.51)	0.013 (0.52)	0.340 (2.54)*	0.041 (2.56)*
Awareness of regulations	-0.140 (-0.74)	-0.016 (-0.77)	-0.307 (-1.32)	-0.036 (-1.42)	-0.216 (-1.48)	-0.025 (-1.56)
Awareness of NEMA regulations	-0.402 (-1.22)	-0.041 (-1.44)	0.897 (2.83)	0.145 (2.31)*	0.210 (0.96)	0.027 (0.9)
Constant	-4.722(-5.03)*		-2.706(-2.26)*		-3.634(-4.88)*	-

Notes: (1) Number of observations: National (3,649); (2) Figures in parentheses are absolute z scores/ratios; (3) An asterisk shows significance at least at the 10 percent level; (4) The Chi-square for the pooled sample is for 8 degrees of freedom.

5.3 Expenditure Thresholds for Adopting and Wanting to AdoptSolar

This last part of the paper provides graphical analysis of the odds for adopting and wanting to switch to solar energy in light of different levels of total household expenditure (as a proxy for income). The aim is to determine the level of total expenditure at which households either adopt or want to switch to solar technologies, using predicted probabilities of such adoption and desire. The graphical representation supplements the logit estimates for the odds of actual and desired installation of solar panels. In this respect, we first examine the total expenditure at which households adopt solar. Secondly, we examine the expenditure level at which households are likely to want to switch to solar. In both cases, we limit the analysis to the national sample. The results are presented in the two panels of graphs presented below.

5.3.1 Tipping Expenditure Point for Solar Adoption

As revealed in Figure 1, the average expenditure at which a household adopts solar is about Ksh.9,887 per month. These numbers, together with those presented in Figure 2, areobtained by getting the antilog of the log of total expenditure. Households have to spend roughly Ksh. 10,000, equivalent to US$116, in order to begin to show interest in solar energy. These figures are very modest by any standards and somewhat mimic those by Lay et al. (2013).

5.3.2 Tipping Expenditure Point for Desire to Switch to Solar

With regard to switching to solar (Figure 2), the total household expenditure for which a household would begin to switch to solar is Ksh.8,103 per month or US$94. The threshold for planned switch to solar energy is even lower than that for actual adoption of solar. This difference perhaps distinguishes between innovators and imitators (Roset and Canals 2011).

Figure 1: Predicted Probability of Adopting Solar Against TotalHousehold Expenditure[9]

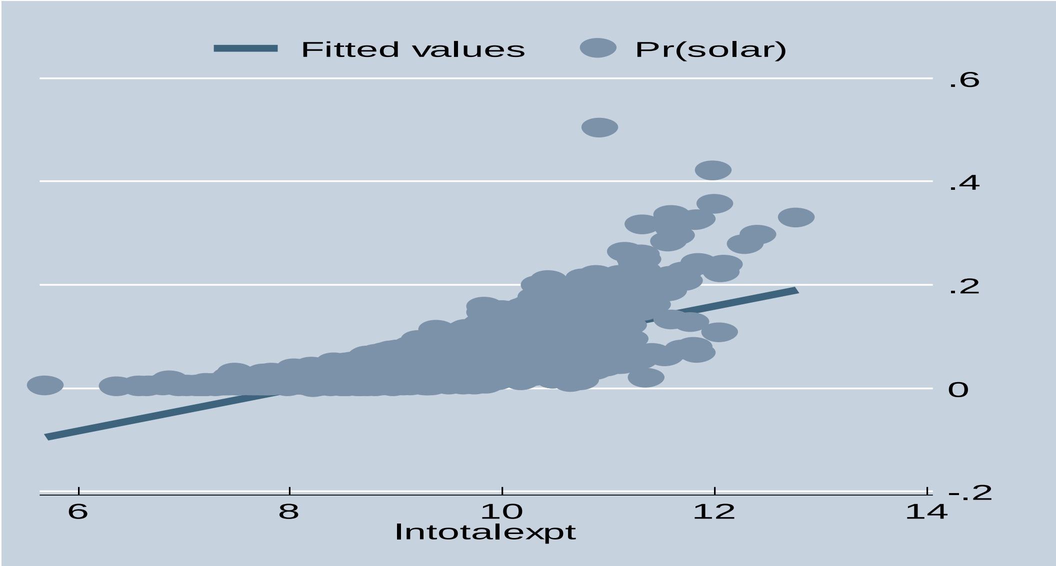
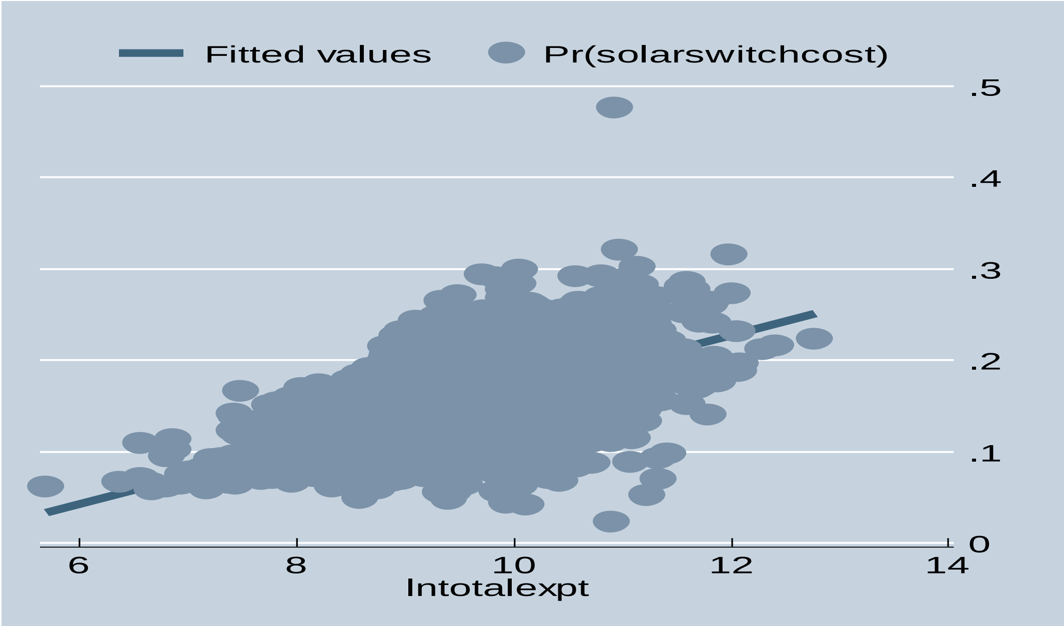


Figure 2: Predicted Probability of Wanting to Switch to Solar Against Total Household Expenditure



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[9] Note that in this and the following figure, the vertical axis shows the predicted likelihood of either adopting or wanting to adopt solar.

6. Summary and Conclusions

Kenya has substantial potential for solar energy because of the very intense solar insolation that the country enjoys. Although solar and other renewable technologies made their debut on the Kenyan scene more than 40 years ago, solar technology has not fully penetrated the local market, despite attempts to popularize such technology. In this paper, we sought to explore impediments to such penetration. Existing literature suggests that delays in technological adoption are outcomes of both supply and demand side forces, and that such adaptation is subject to learning-by-doing effects and expectations about future reductions in the costs of the technology. Technological diffusion also depends on the attributes of the population and the distribution of innovators and adopters.

Applying discrete choice models to existing energy survey data sets, we have demonstrated that solar energy is an important source of electric energy for lighting, especially in rural Kenya. The results also suggest that progressive personal attributes of household heads, as well as general household well-being, are important predictors of the odds for installing solar panels and the likelihood of planning to switch to solar energy as the primary source of lighting energy. Income and formal employment by household heads are key predictors of the odds for not only adopting but planning to switch to solar energy for lighting purposes. There is a critical level of household prosperity necessary for ‘take off’ into solar technologies. However, that level appears lower for planning to adopt than for actually adopting solar. In any case, adopting and planning to adopt solar energy are threshold decisions that are likely to increase with a general improvement in general prosperity, particularly in rural areas, where solar energy is attractive because electricity grids may not reach such areas. This means that policies with potential for increasing general welfare for Kenyans, such as those targeting poverty reduction and employment creation, are a boon for uptake of solar technology.

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