Energy Efficiency (2018) 11:663–681
https://doi.org/10.1007/s12053-017-9590-8

ORIGINAL ARTICLE

The impact of microhydroelectricity on household welfare indicators

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Received: 18 December 2016 / Accepted: 29 September 2017 / Published online: 27 December 2017

Abstract The use of small-scale off-grid renewable energy for rural electrification is now seen as part of the sustainable energy solutions. The expectation from such small-scale investment is that it can meet the basic energy needs of a household and subsequently improve some aspects of household welfare. However, these stated benefits remain largely hypothetical because there are data and methodological challenges in existing literature attempting to isolate such impact. This paper uses field data from microhydro schemes in Kenya, and propensity score matching technique to demonstrate such an impact. We find that on average, households connected to microhydroelectricity consume 1.5 l less of kerosene per month compared to households without any such electricity connection. In addition, non-connected households spend 0.92 USD more for recharging their cell phone batteries per month in comparison to those who were using microhydroelectricity service. Finally, school children from households that are connected to microhydroelectricity were found to devote 43 min less on evening studies compared to those without electricity. The findings provide interesting insights to some of the claims made for or against use of off grid renewable energy for rural electrification.

Keywords Microhydro · Rural electrification · Impact · Kenya

JEL classifications C21 · Q01 · Q42

Introduction

The International Energy Agency estimates that 1.2 billion people in the world had no electricity access by the year 2013 (IEA 2015). Slightly more than half of these people are in Sub-Saharan Africa (SSA), making electricity access a particularly pressing development problem in this region. Consequently, there have been concerted efforts to direct more infrastructure spending to rural electrification (RE) mainly through grid extension and other alternatives like renewable energy microgrids. For instance, the World Bank is currently running several lending programs for rural electrification in developing countries. Although not widely deployed in SSA before, microgrids are now important in deploying renewable energy in remote rural areas where grid extension is uneconomical (Munuswamy et al. 2011). Among the many advantages of microgrids over national grid are the lower energy losses during transportation, since

This article is part of the Topical Collection: Energy and Climate Economic Modeling
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electricity generation occurs near the consumers (Abu-Sharkh et al. 2006). Such systems are also useful means of energy conservation practices because they reduce demand on grid-provided electricity (Casillas and Kammen 2011). The main justification for these rural electrification interventions is based on a hypothesis that access to electricity can lead to improved health, education, gender equality, and economic outcomes. Bernard (2010) observes that in the face of current resource shortages and competing budgetary needs, it is important to account for rural electrification spending in improvement of human living standards. This is the entry point for academic literature that sets to obtain the independent impact of rural electrification on several claimed outcomes.

Barnes and Binswanger (1986) note that RE projects take long to materialize in addition to the fact that rural households may take long to make the connection or adoption decision. Consequently, the socio-economic benefits may take long to show up even if a lot of unrecoverable resources have already been spent. Methodological difficulties are apparent in literature given that the most suitable methods of establishing impact like randomized control trials (RCTs) may not be easily applicable. This is because electrification projects in developing countries are mostly subsidized, and the fact that isolating treatment and control groups in electrification of poor households may raise ethical challenges. Despite these difficulties, several attempts have been made in literature to quantify the changes that occur to grid electricity consumers. Increased income is established by Khandker et al. (2012, 2013), but this may only be a localized impact as shown by other studies like Bensch et al. (2011). Thus, it is not a guarantee that households in all electrified geographical regions will get an income gain attributable to electrification. Other studies like Dinkelman (2011) have established an increase in employment that is purely attributable to electrification.

Gender equality objectives may be achieved if availability of electricity eases household chores that mainly tend to tie women down, such as cooking with collected firewood (Dinkelman 2011). However, this impact may not occur in countries where electricity is expensive and households limit their use of electricity to only light uses (Madubansi and Shackleton 2006). Educational gains from rural electrification can only be established in samples that include children and teenagers who go to school, and even so the proxy used for education gain is study hours which may not translate into improved academic performance. Bensch et al. (2011) find non-robust evidence of increased study time for primary school kids in rural Rwanda, while Matinga and Annegarn (2013) caution that access to electricity may paradoxically reduce the study time as children divert study time to electricity-aided entertainment activities. This indicates that a case-by-case assessment of electrification intervention impacts may be particularly necessary. More importantly, renewable energy microgrids may deliver services that are slightly different from grid services, and there are no grounds for assuming that impacts on microgrid consumers are similar to those of grid consumers.

There is a general hypothesis that access to electricity leads to elimination of dirty fuels, driven mainly by the replacement of kerosene lamp and open fires with electric bulbs. Madubansi and Shackleton (2006) find that electrification led to increased fuel wood use in households, although they do not control for other changes to a household over time. Even so, we cannot entirely dismiss such an outcome given that rural households may not afford the cost of cooking with electricity. The obvious thing in the literature is that electricity can affect different aspects of human welfare, all of which are agreeably important. More importantly, it is apparent that the impact of electrification is context-dependent and difficult to generalize. Since off-grid renewable electrification solutions are potentially different from grid services in terms of quality (Terrado et al. 2008), it is clear that expectations from such installations are more likely to be modest but all the same useful.

While electrification impacts resulting from grid extension dominate empirical literature (see Bernard 2010; Dinkelman 2011; Khandker et al. 2012, 2013), there is a dearth of empirical evidence for the impacts of alternative off-grid rural electrification. Off-grid renewable energy is often justified on the basis that it leads to improvements of human welfare such as provision of convenient, affordable and clean electricity. This remains an empirical question because the few studies that claim such impact do not solve for self-selection bias into connectivity (see Madubansi and Shackleton 2007; Komatsu et al. 2011; Mondal and Klein 2011; Matinga and Annegarn 2013). Moreover, evidence from ex-ante evaluation like Bensch et al. (2012) may not be very informative on the impact of limited capacity electrification interventions, since they use households connected to grid supply for comparison purposes. In this paper, we contribute to the ongoing debate about deploying off-grid renewable energy electrification by using observational data and a consistent estimation that can permit attribution of electrification to outcomes. The main objective here is to establish the impact of connecting to limited off-grid electricity source to selected indicators of household welfare.

Microhydroelectricity and rural electrification in Kenya

Although there have been ongoing rural electrification investments in Kenya, serious state focus on rural electrification can be traced back in 2003 in the advent of a political regime change. Several changes in the electricity sub-sector culminated into adjustments in the Energy Act and a sessional paper on energy that recommended separating of generation and distribution functions, as well as introduction of energy sector regulator in 2006. Other players have been introduced through review of the energy sector policy and regulations. The function of rural electrification is the responsibility of the Rural Electrification Authority (REA), while power generation and distribution are left to Kenya Electricity Generation Company and Kenya Power and Lighting Company, respectively.

Responsibilities for renewable energy development are spread across actors in the energy sector with the government's role being largely facilitation through policy. Despite this type of institutional set up, electricity access continues to be a development challenge with only 7% of the rural population having access to electricity.[1]

The use of off-grid renewable energy technologies like microgrids based on solar, wind, and water has been adopted by individuals, communities, and institutions as alternative RE mechanisms in Kenya. These are mainly put up by private individuals (like solar home systems or individual microgrids) or communities (microsolar/hydro grids) to either meet their primary energy needs or supplement other energy sources. Community-owned microhydro grids is one such alternative, whose origin is two demonstration projects set up by the Government of Kenya in conjunction with development partners (United Nations Development Programme and Practical Action) back in the year 2000. Two communities were mobilized to set up microhydro grids that would later act as technology references for other groups. What followed was a long trial period, and the demand for this alternative electrification remains high even in places that have grid presence, but state support for such local electrification projects has reduced. The latter has not dampened the interest of community-based projects with at least 10 proposals lined up for potential funding, while others are at various stages of development.

Once a community decided to exploit local microhydro potential, a scheme would be established, and participating households within the radius of a microhydro would be required to register on a first come basis. Communal manual work and contribution of building materials and money form part of the mandatory contributions throughout the phases of constructing the power plants and distribution lines. Only those who have fulfilled all the labor and financial obligations are eligible for connection of power into the households in several phases. Because of financial or technical limitations, most community microhydro grids in Kenya are designed to provide basic electricity services to member households ranging from lighting to powering small appliances like televisions. As a result of this limited use, one would not expect outcomes associated with heavy use of electricity like cooking or pumping. An interesting observation is that households connected to the grid in these rural areas limit electricity use to similar light uses due to affordability issues and availability of other cheaper alternatives. Nevertheless, it is important to isolate the claimed impact of microgrid electrification in literature since they inform the investment decision in the first place. This study seeks to establish such impact using observational data collected from participating and non-participating rural households in established community-based microhydro schemes.

Literature review

Impact evaluation studies for electrification and other infrastructure projects have only become popular recently, following accountability concerns by the donor community (Bernard 2010), especially after the Paris Declaration on Aid Effectiveness. The existing studies on impact evaluation of rural electrification can be classified into those that use mainly attributions to claim impact and those which put emphasis on addressing endogeneity (participation bias) while seeking causal impact. The first lot of studies collect post-electrification data to describe how consumers look like after electrification, or compare outcomes based on whether one has electricity or not. The limitation with these studies is that the claimed benefits such as

[1] Based on 2015 World Energy Outlook Database

extended night activity and clean indoor air cannot be attributed to electricity access only, since the environment under which they are isolating impact is not controlled from other influences. This weakness is addressed by studies that create experimental atmosphere or try to mimic one, which permits a claim of causal impact of electrification. Both studies are reviewed here with this setting in mind.

The most obvious way of telling that a household has benefited from electrification is through extended night activity, due to availability of more quality and efficient lighting (Bensch et al. 2011). Most studies assume away this impact which may not be achieved if electrification is accompanied by poor service like extreme outages. Bensch et al. (2011) find that connected households in Rwanda report more light hours per day compared to their counterparts who are not connected. The measure used here does not account for the fact that more light hours from use of for instance tin lamps is a non-desirable outcome due to the associated pollution. It may be worthwhile to look at other ways of capturing increased use of lighting in the household from electrification, since demand for lighting during the day is very little for rural households. For instance, the use of either kerosene or firewood for lighting is costly to the household and inconvenient due to smoke, and it is reasonable to expect that cheaper and cleaner option like microhydroelectricity would be associated with more use of light at night. Thus, comparing the night time light hours may be more useful as opposed to looking at whole day light usage.

Reduced consumption of dirty fuels like kerosene and fuel wood is a common justification for rural electrification, but the assessment from empirical work is contentious. Dinkelman (2011) found that households' take up of electric cooking and lighting led to reduced use of firewood over a six-year period (1996–2001) of rural electrification in South Africa's Kwa Zulu Natal Province. However, Madubansi and Shackleton (2007) contend that in some communities of Bushbuckridge within South Africa, fuel wood use did not decrease in the aftermath of rural electrification carried out between 1991 and 2002. Elsewhere, Vietnamese households experienced huge reductions in kerosene lighting after only 2 years of electrification in a country with a high grid reliability (Khandker et al. 2013). However, if electricity supply comes with frequent power outages, electrified households end up spending the same amount on kerosene as those who are not electrified as found by Khandker et al. (2012) in Bangladesh. Complete elimination of kerosene in the household is also possible, as illustrated by the introduction of Solar Home Systems (SHS) in Bangladesh (Mondal and Klein 2011). This happens when households become so accustomed to clean indoor air after electrification that they find it inconceivable to revert to kerosene use and experience the associated smoke. Elsewhere, Bernard (2010) observes that although rural households desire to use electricity for activities such as cooking, a combination of cost/affordability ensures that cheaper options like firewood eventually prevail. Thus, health gains from electrification such as those demonstrated by Rollin et al. (2004) among South African households may not be achieved unless rural electrification is accompanied by programs disseminating cleaner household fuel alternatives. One can safely predict that rural electrification can only reduce rather than eliminate the use of dirty fuels in the household.

Economic gains from electrification accrue from increased productivity in home enterprises or intensification of agricultural activity. In Vietnam, adoption of electric water pumps was observed to have replaced manual irrigation leading to increased agricultural income (Khandker et al. 2013). Electric water pumps enable farmers to irrigate larger acreages of land with little spending on labor, and this may translate into higher earnings if markets are accessible. Bensch et al. (2011) find that electrified houses have slightly more income in Rwanda. This outcome is from an ex-ante evaluation under the assumption that hypothetically connected households would reap the same benefits as those already connected. However, Matinga and Annegarn (2013) caution against such assumptions that lead to generalizations in impact evaluation work. The study notes that income gains from electrification are largely dependent on pre-existing conditions or simultaneous interventions which are rarely captured in observational data, and this is responsible for the varying outcomes in literature. For instance, if electricity service is of limited capacity or comes with poor service, then the probability of zero income gain is even higher. Alongside this reasoning, Rao (2013) finds that although electrification led to higher incomes in Indian villages, those households with better quality of supply had even higher income gains. This resonates with our earlier claim about expected gains with limited capacity rural electrification. Other conditions like markets and level of economic activity determine the potential income gain. Bernard (2010) observes that in SSA rural settings, there is limited employment opportunity exacerbated by lack of market for goods that are produced by home enterprises. Electrification may lead to increased productivity of microenterprises such as that described by Jacobson (2007); Kirubi et al. (2009) in Kenya, but income gains may not be realized due to market bottlenecks. Obermaier et al. (2012) advises that for electrification programs to be successful, they must be integrated into the greater rural development strategy. The twin objectives of increasing access as well as increasing electricity consumption through other facilitation programs must be met in addition to simultaneously implementing other non-electrification programs. These other supporting programs may take time to implement, giving long lead times for income gains to be observed after electrification. Khandker et al. (2009) found that in Bangladesh, income gains from electrification increased with duration of electricity exposure but at a decreasing rate (based on the squared term for duration electrification). Income thus seems to be one of those benefits that can be accessed only in the long term after and electrification intervention.

Gender-based roles are common in developing countries cultural settings, and they may have a bearing on who gains most from electrification within a household. For instance, women spend time collecting firewood for family use and introduction of electricity may reduce the demand for firewood subsequently freeing up some of their time. This additional time may be translated into increased labor market participation by women, as observed in South African rural households by Dinkelman (2011). Most rural households however continue to use firewood and charcoal for cooking even after electrification, with an enormous 80% of rural electricity consumption devoted to lighting and television (see Kohlin et al. 2011). The inability to pay for more units of electricity, cultural cooking habits or simply inadequate delivered quality of electricity to be applied to some uses may mean that expecting such gender-related outcome is farfetched in developing countries. Results for educational gains from electrification are mixed. Although electricity avails quality light for reading in the evening, Matinga and Annegarn (2013) note that children may reduce their daytime study hours by taking up television watching or playing games. Thus, there is no direct link between electrification and education outcomes because more often than not, there is no long-term data to indicate if the changes in study patterns actually translate into education outcomes. In an interesting case, rural electrification resulted in an observed increase in school enrolment rates and average years of schooling for girls in India between the years 1982 and 1999, while no such significant change was observed for boys (Van de Walle et al. 2013). In Bangladesh, Khandker et al. (2009) find that electrification led to an increase in both study hours and school completion rates with boys appearing to have gained more than girls. Within each gender, education gains from electrification were higher in households with more land. This implies that more resources (like capital) may lead to higher gains from electrification because they possess higher ability to pay for other services.

In addition to the above contradicting outcomes from rural electrification, a major concern in empirical work is the methodological approaches mainly driven by endogeneity/sample selection problems and data availability. Households that are naturally flexible and hardworking are more likely to self-select into connection, and this means that they are likely to have better outcomes than their rigid or less determined counterparts even in the absence of electrification. Additionally, placement of rural electrification projects is usually biased towards areas with higher economic potential due to concerns about project returns. Studies vary in their econometric approaches that allow a claim about causality. More importantly, data availability dictates the choice of method particularly where evaluation is not a component of rural electrification programs. Propensity score matching as used by Khandker et al. (2009); Bensch et al. (2011) seems more appropriate in the absence of before and after connection data, with the major challenge being finding proper and adequate comparison units. The use of geographical instrumental variables on the other hand is gaining popularity in literature, making it a feasible approach whenever such data is available. Dinkelman (2011) uses community gradient in a study of communes distributed in South Africa's province of Kwa Zulu Natal to establish the labor market gains from electrification, while the distance from nearest connectivity point in India is used as an instrument for endogenous electricity access in India (Khandker et al. 2009). In special cases where data spanning two time periods is available, adopting panel-fixed effects can control for selection problems, in addition to identifying long-term benefits of electrification. Such data is missing in most instances for small-scale projects. However, published literature that has looked at that scale of electrification (Kirubi et al. 2009; Komatsu et al. 2011) adopts approaches that cannot support causality and claimed impacts, and there is a need to re-assess the impacts using more robust approaches. Furthermore, since return-based targeting that is popular with grid electrification is rarely the motivation behind village microgrids, one needs to be conservative with the choice of outcome selection for impact analysis (Matinga and Annegarn 2013).

Overall, literature provides some lessons on potential benefits of both grid and off-grid rural electrification. It is apparent that the quality of electricity delivered to a household determines what power can be used for, and thus the consequent gains. Because most studies that claim causal impacts consider grid electrification, they do not offer lessons for small projects which deliver limited capacity electrification. There are nevertheless expected benefits from such projects, whose evidence forms the goal of this study. Considering data challenges raised above, the next section looks at a feasible strategy that can allow us to identify such impacts.

Methodology

This section addresses the econometric procedures to deal with endogeneity of household connection to a village microhydro grid, which will then allow for a claim of impact. The problem of impact evaluation is explained, leading to a choice of method appropriate for the current study. The data used for the study is then described, followed by the estimation procedures.

Theory of impact evaluation and propensity score matching

According to Caliendo and Kopeinig (2008), the mainstay of any impact evaluation exercise is establishing how a treated individual would look like if they never got the particular intervention or the "treatment effect." The latter is the causal effect of a binary event on an outcome of interest to a researcher. The Roy-Rubin framework provides an approach to defining this causal inference problem with the main components being treatment (connection) status; potential outcomes (on kerosene spending, battery charging expenses, and light usage at night); and the subjects (households). Following exposition of this model in Caliendo and Kopeinig (2008), consider the treatment indicator D and the subject i, so that the treatment indicator of a subject is denoted by D_i. D_i assumes a value of 1 if subject i (where $i = 1, 2, 3,...K$) was exposed to the treatment and a value of 0 if the subject has not been exposed to treatment. Defining Y_i as the potential outcome of the subject, then $Y_i(D_i)$ denotes the potential outcome of a subject i from its treatment status.

The treatment effect t_i is the difference between the outcome of an individual with treatment and without treatment, i.e.:

$$t_i = Y_i\ (D = 1) - Y_i\ (D = 0). \tag{1}$$

Obtaining this value requires us to observe the same individual i under the two states, so that we compute the individual treatment effect on the treated (average treatment effect, ATT).[2] This is impossible because the treatment cannot be removed from the subject once given, so an ATT based on the population of interest is used as an approximation as follows:

$$\begin{aligned} t_{\mathrm{ATT}} &= E\ (t|D = 1) \\ &= E\ [Y\ (1)\ |D = 1] - E[Y\ (0)|D = 1] \end{aligned} \tag{2}$$

where $E\ [Y\ (0)\ |D = 1]$ is the counterfactual or the outcome of a treated subject if he/she had not received the treatment. However, the component $E\ [Y\ (0)\ |D = 1]$ is still not recoverable and this is what leads to a counterfactual problem.

For experimental studies like RCTs, using $E\ [Y\ (0)\ |D = 0]$ as an alternative provides valid estimates of treatment effect since randomizing subjects into treatment and control groups ensures that there is no self-selection into the treatment. However, the same cannot be said in the absence of randomization. This is because there are factors that could be affecting both treatment and outcome simultaneously, so that the outcome variable would still be different for the two groups even if treatment was not administered in the first place. This is one source of identification problem in evaluation work. The "self-selection bias" can be illustrated by rearranging the expression for ATT as follows:

$$\begin{aligned} &E\ [Y\ (1)\ |D = 1] - E\ [Y\ (0)\ |D = 0] \\ &\quad = t_{ATT} + E\ [Y\ (0)|D = 1] - E[Y\ (0)|D = 0] \end{aligned} \tag{3}$$

[2] Although ATT is the most commonly used measure, another possible measure is the ATE (average treatment effect) useful if the treatment is applicable to general population.

An unbiased treatment effect on the treated can only be obtained if the "selection bias" term amounts to nil as follows:

$$E\left[Y\ (0)\ |D=1\right]-E\left[Y\ (0)\ |D=0\right]=0 \quad (4)$$

Experimental studies ensure that the difference between the counterfactual terms for treated subjects and the observed outcome for control subjects is 0. In the absence of randomized control trials, there are methods of impact evaluation that employ techniques to reduce these differences. Depending on data availability, several statistical techniques can be used to reduce this bias: regression methods, instrumental variables, propensity score matching-based methods.

Propensity score matching method

According to Rosenbaum and Rubin (1983), a propensity score Pr $(D=1|X)$ is the predicted probability of assignment to the treatment $(D=1)$ conditional on a vector of observable X. Since it is a balancing score then it allows us to group subjects into treatment $(D=1)$ and control $(D=0)$ such that we can derive sensible comparisons between them. Balancing scores are a function of the observable characteristics and it has been shown that if treatment is ignorable (or unconfounded)[3] given X then it is also ignorable given Pr (X) (see proof in Rosenbaum and Rubin 1983), and comparing the mean outcomes of treatment and control subjects at each value of score yields unbiased treatment effect. For small samples, the propensity score is estimated using a probit or logit model. The resultant propensities can then be applied differently to adjust observations such that comparison is possible in three major steps: 1) creating matched samples from the control subjects; 2) constructing sub-classes of similar units; and 3) comparing the impacts within those sub-categories to come up with the differences. Subject to the availability of adequate control units, matching is more practical and popular in studies than the other two methods highlighted in the previous sub-section.

[3] Treatment ignorability/unconfoundedness is one of the conditions for using PSM. It states that if we obtain a set of observable characteristics that are independent of treatment assignment, then outcome is independent of treatment assignment (see Caliendo and Kopeinig 2008). The other requirement for PSM is the overlap condition, $0 < Pr(D=1|X) < 1$, which requires that subjects with the same characteristics have a positive probability of being in both treatment and control groups.

The first step in carrying out propensity score matching (PSM) is to estimate the scores using a choice model and obtain the predicted probability of a subject receiving treatment conditional on X. Given that two conditions of treatment (ignorability and overlap) are met, the average treatment effect on the treated subjects using PSM is expressed as follows:

$$t_{\mathrm{ATT(PSM)}} = E_{(\Pr(X)|D=1)}\left\{E\left[Y\ (1)|D=1,\Pr(X)\right]-E[Y\ (0)|D=0,\Pr(X)]\right\} \quad (5)$$

where $E_{(\Pr(X)|D=1)}$ is the distribution of the subjects' propensity score that is used as a weight of the difference between the outcome of the treated and untreated subjects within the region of overlap. But first is a statement of the link between the treatment and the expected outcomes.

Change mechanism

The change mechanism is basically what follows after any electrification program: once a microhydroelectricity potential is taken up by a community for development, some households join the scheme and subsequently contribute the relevant financial and labor obligations. The harnessed electricity is then connected to households who have fulfilled the contributory obligations while others drop out of the scheme or do not join the scheme in the first place. In a previous section, it was highlighted that microhydroelectricity has limited applications in the household level. Therefore, it would be reasonable to expect outcomes that are associated with the use of low voltage items in the household that comprises of mainly lighting and small appliances.

Kerosene is the primary source of lighting in 68.93% of Kenyan households, and the prevalence of kerosene lighting is higher in rural areas compared to urban areas.[4] Ngui et al. (2011) highlight that while kerosene is mainly used for cooking in poor urban households, its main use in the rural household is lighting. The first use of electricity in a household is to replace kerosene as a primary lighting fuel. The expectation here is that households connected to microgrids have a lower average consumption of kerosene in terms of both the

[4] see data at https://www.opendata.go.ke/Distribution-and-Consumption/Main-LightingEnergy-Sources-averaged-to-Counties-/g9hi-bs9n

physical quantities and spending. Kenya is a net importer of crude oil products and the fluctuations in the price of these products affect households using kerosene as a primary energy source directly. This is the reason behind the controversial subsidy on kerosene in Kenya, and it would be interesting to establish if microgrid electrification reduces kerosene consumption.

Secondly, Bensch et al. (2011) propose that the number of lighting hours is an important indicator of the impact of any electrification project, as it is a primary indicator of the level of service take up. The expectation here is that connected households experience more light hours (for our case, we choose to limit ourselves to hours of light during the night) than those not connected because the latter have to limit the use of more expensive kerosene fuel. School-going children would also be expected to increase their evening study time due to availability of electricity. Lastly, the ability to use information and communication appliances like radios, televisions, and mobile phones is more enhanced if there is power connectivity in the household. High spending on recharging the batteries for use with these devices is likely to impede their utilization, and this has a negative effect on the household (Komatsu et al. 2011). If there is electricity connection in the household, there is less spending on recharging batteries and this extends the time of use of the devices. This also means that the device can be used whenever the owner needs it. Table 1 in the Appendix summarizes the outcomes of interest for this study, and their measurements using the methods described in the next section.

Empirical strategy

Data collection

This exercise involved comparing outcomes of households that are connected to community microgrids to those with no connection to microhydro scheme electricity service. There was no comprehensive list of microhydro schemes in Kenya by the time we conducted this study. For identification of projects that would consist of connected households, we used a list of functional projects from a recent scoping study on microhydroelectricity use in Kenya spread over three counties in central Kenya: Muranga, Nyeri, and Kirinyaga. Unfortunately, there were plants that were listed as functional but generation had stopped long ago. As a result, all schemes were visited by the researcher before classifying them as functional or non-functional with regard to production and distribution of electricity. Because of the limited number of connected households that were found, it was important to interview all the connected households in every scheme. A total of 77 connected households were available for interview spread across four functional schemes, while some 15 household heads could not be interviewed because they were not present during the time of the survey. There are both connected households and those that are not connected in every scheme environment. The latter provided good potential matches for the former, since they face the same fairly similar conditions. Due to the technical requirements for microhydroelectricity generation, all schemes are located in very similar geographical and climatic zones (in rural areas, near water towers, similar agricultural potential, and in highland climatic conditions), and the households face near similar economic opportunities. The control households were randomly picked from the pool of non-connected households within the defined radius of a microhydro scheme, while leaving out the grid-connected households. Following this procedure, a total of 190 control households that had no electricity connection were interviewed.

Estimating the propensity scores

For estimating the propensity scores, Caliendo and Kopeinig (2008) and Zhao (2008) among others indicate that there is no foundation for discriminating between the logit or probit specifications. This is because if the unconfoundedness condition is met, the estimated impacts from the two models are very similar. The choice of covariates in the connection status model was informed by advice in Garrido et al. (2014); Bensch et al. (2011); Caliendo and Kopeinig (2008). Generally, variables that are thought to influence both treatment and outcome should be included, while leaving out those that may be influenced by treatment. Thus, economic theory, intuition based on the knowledge of research area, and past research should form the criteria of choosing variables. This study relied on the first two criteria, and the following observable characteristics are proposed to predict the connection decision, for purposes of estimating the propensity score. There are some differences in the means of these characteristics between the two groups (see Table 2).

X = {household size; gender of household; employment status; having received environmental training; type of dwelling; kerosene price; monthly income and age of household}[5]

The probability that a household is connected to a microhydroelectricity is the $E(Y=1)$ and it is a linear function of X as follows:

$$E(\mathrm{Y}=1)=\Pr[Y=1|X]=\alpha X_i \tag{6}$$

where α denotes the regression coefficients. For a binary outcome model (logit), this is a non-linear model and $F = \sum \alpha X_i$

$$\Pr[y=1|X]=\frac{\exp\{F\}}{1+\exp\{F\}} \tag{7}$$

is the cumulative density function of the logistic distribution.[6] The propensity scores (predicted probabilities) based on (6) therefore fall between 0 and 1.

From the "Propensity score matching method" section, it was highlighted that one of the conditions for estimation of ATT is the presence of overlap or common support region in data. This will ensure that subjects with the same propensity scores have a chance of either being connected to the microhydro grid or not. The best way to demonstrate the existence is through visualization using density plots (see Fig. 1 in the Appendix).

Matching quality

Once the propensity scores have been estimated, the next step involves stratification to make sure that in each stratum both treated and control subjects have "similar" propensity score. From "Propensity score matching method" section, it was indicated that a propensity score is actually a balancing score. This implies that within each strata of propensity score, the treated and control subjects should be having the same distribution of observed covariates for them to be comparable. According to Austin (2011), one way of ensuring that the model for estimating that the propensity scores was well specified is to ascertain whether the distribution of the covariates for the two groups is similar within the matched sample (same stratum). For a set of matched subjects, the probabilities of being in either treatment category are equal, that is:

$$\Pr\ (D=1|X)=\Pr(D=0|X) \tag{8}$$

Several methods have been proposed in literature to check to balancing quality after matching (Austin 2011). The use of standardized differences in the means seems to be superior and was adopted by this study. The standardized differences in means for a continuous variable are calculated as given below:

$$d=\frac{\overline{x}_{treatment}-\overline{x}_{control}}{\sqrt{\frac{s^2_{treatment}+s^2_{control}}{2}}} \tag{9}$$

while that of a binary outcome variable is given as follows:

$$d=\frac{\hat{P}_{treatment}-\hat{P}_{control}}{\sqrt{\frac{\hat{P}_{treatment}\left(1-\hat{P}_{treatment}\right)+\hat{P}_{control}\left(1-\hat{P}_{control}\right)}{2}}} \tag{10}$$

where d is reported as standardized percentage bias in the results.

The one thing that is clear in literature is that it is difficult to expect balance in all the covariates, and there is no standard for the "tolerable" imbalance.

However, it is erroneous to claim an impact if you have "bad" matches (see Garrido et al. 2014; Austin 2011 among others). Other methods like the use of t-tests and model fit measures have been discredited due to disconnection between their major assumptions and the purpose for which propensity scores are estimated.

Choice of matching methods

The general framework for PSM estimator for ATT was shown in "Propensity score matching method" section. Once a balanced propensity score is obtained, a matching method with which to use the propensity scores is chosen. Several matching estimators work by comparing the outcomes of the connected

[5] Naïve regressions of treatment dummy and these predictors on each outcome were conducted, and they portray some unexpected impacts (signs of treatment dummy coefficient), or over(under)estimation of the size of impacts if proper impact evaluation technique is ignored (see results in Table 3 in the Appendix).

[6] For the case of a probit, this becomes the CDF for the standard normal distribution

households to that of households which are not connected. The matching techniques vary according the following: handling the common support requirement, defining the appropriate distance between two comparison subjects (neighbors), and the weighting of each comparison unit (Caliendo and Kopeinig 2008). The choice of a method depends on the data available and involves a "bias-efficiency" trade off. Two methods were adopted for this study based on the type of data available to us, namely, kernel and nearest neighbor matching.

Kernel matching

The study chose the kernel matching as the base comparison model, given the limitations of getting too many observations as controls in the sample. This technique allocates a weight to each control within a pre-defined range (bandwidth) depending on how "close" that subject is to a treated subject. Therefore, control subjects who are closer to the treated ones in terms of propensity scores are allocated more weight than those who are distant. A bandwidth width of 0.06 was used based on literature because it is optimal in the trade off between efficiency and bias. For robustness checks, lower (0.04) and higher (0.08) bandwidths were also be considered. The downside of kernel matching is that it can introduce a bias, while improving on efficiency. To overcome this, estimation is limited to the common support region and we use nearest neighbor estimator which is inefficient but introduces less bias as a "robustness" check (see Caliendo and Kopeinig 2008).

Nearest neighbor matching

This estimator involves picking 1: k treated and control subjects who have smallest propensity score difference. The matched controls can be replaced back in the reservoir of control units and used as matches for another treated unit, and this estimator is called "NN with replacement." The use of replacement is adopted for this study because it improves the quality of matching (Caliendo and Kopeinig 2008), given the limited number of control observations that we have. We also use calipers to safeguard against poor matches in instances where the nearest neighbor may be too distant from its treated counterpart in terms of propensity score (Garrido et al. 2014).

Sensitivity analysis

From "Propensity score matching method" section, the assumption of unconfoundedness was adapted to allow us to use the matching framework. This means that we can observe all the covariates that affect both assignment into the connection status and outcomes of interest. However, this may not be potentially true and according to Caliendo and Kopeinig (2008) matching estimators such as those adopted by this study may not be robust to such an eventuality. Rosenbaum (2002) provides a model of sensitivity analysis against this "hidden bias" based on a parameter that indicates the extent of deviation from random assignment of objects to treatment. A hidden bias is said to be present if two households i and j with similar observable characteristics X have different chances of connecting to the microhydro service θ. Rosenbaum (2002) relates the odds ratio of such two households to a parameter Γ representing the effect of the observable characteristics on the selection into connection decision as follows:

$$\frac{1}{\Gamma} \leq \frac{\theta_i \left(1-\theta_j\right)}{\theta_j \left(1-\theta_i\right)} \leq I \forall i, j \tag{11}$$

For the classical case of randomization, this parameter takes the value of the following:

1. If the value of this parameter increases by a certain factor (γ) of for instance 0.2, then the odds of these two similar households being connected could differ, so that now i is more likely to be connected than j by a factor of 1.2 despite the two households appearing to be similar to us based on X. This difference is attributed to the unobservable factors (γ is the reaction of the connection status to changes in some unobservable characteristics). Effectively, the test allows us to determine how strongly observable covariates must affect the selection into treatment to a point of compromising the consequences of the matching. Results are said to be sensitive if an increase in γ makes the inference different from that obtained while assuming that $\gamma = 0$ (that is no hidden bias). Insensitive results imply that a very big γ is required to alter the base inference.

Results

Data description

The treated and control subjects are similar in only 5 out of 10 characteristics (see Table 2 in the Appendix). Based on this outcome, we conclude that it is important to address the fact that these two groups have other potential differences apart from the treatment status. The differences in the outcome variables between the two groups based on naive *t*-tests are also shown in Table 2.

Propensity score estimation model

From Table 4 (see Appendix), having a male household head and a non-permanent living structure is associated with a lower probability of being connected to a microhydro grid service. It is apparent that household size, farm size, piped water connection, and age are not relevant in explaining the treatment status of the households in the sample. However, they have theoretical relevance to connection status and their inclusion into the model did not result into adverse matching quality. The goal of the logit estimation in this case is to obtain propensity scores for matching as opposed to offering a structural explanation of the connection decision. A propensity score was therefore estimated from the predicted probability of connection given by this model and used to select comparison subjects in next stage. The distribution of the propensity scores between the connected and unconnected households is shown in Figs. 2 in the Appendix. A stratification of the propensity scores was done, with the optimal number of blocks suitable for the data determined as 5 within the common support the overall indication was that the balancing property was satisfied. The next thing is to check if there exist comparable units within the data.

Region of common support and matching quality

The propensity score was used for matching using two methods: kernel and nearest neighbor (NN) matching. The specifications which gave the best matching quality in terms of both mean and median standardized differences in covariates were kernel (Epanechnikov) with a bandwidth width of 0.06 and NN with two neighbors and caliper of 0.25. There were no reported bad matches and the Rubin's *r* (this test is based on the standardized differences) was within the expected range for good matches. The findings from the estimated ATTs are discussed in the next section.

Treatment effect using kernel matching

Significant effects of electrification through microgrids were found for the quantity of kerosene consumed per month, spending on charging mobile phone batteries per month, and the number of hours that children dedicate to studies in the evening. There is no significant difference in both the hours of light at night and radio entertainment between connected and non-connected households. The results were robust to changes in bandwidth changes as well as to use of nearest neighbor matching with several calipers. No bad matches were reported by the standardized difference of means ratios. The sensitivity analysis implemented using code provided by Gangl (2004), and the implication from the test is that obtained impacts are insensitive to changes in the assumption we made on unconfoundedness (see result in Tables 6 and 8 in the appendix). Therefore, matching gives us a fair indication of what is happening in the sample.

The treatment effect is significant for only three outcomes: the physical quantity of kerosene consumed per week, the expenditure incurred on cell phone battery recharging, and the number of hours that kids study in the evening. However, there is no difference between connected and unconnected households in terms of the following: the proportion of spending on kerosene, the number of night light hours, and the length of time that radios are utilized in the households. The following section gives a contextual interpretation of the significantly different outcomes.

While households which are not connected to the microgrid consume about 2.8 l of kerosene per month, the connected households consume about 1.3 l resulting to a difference of approximately 1.5 that is reported in column (a) in Table 5. The explanation for the 1.3 l of kerosene consumed by the connected households is due to frequent repairs or breakdowns that were reported in most plants. Therefore, these households are forced to purchase kerosene as a contingency during service outages.

No household in our sample was found to be using kerosene for cooking, thus we cannot attribute the utilization of kerosene by electrified households to cooking. More important is the fact that even with such breakdowns, connected households still manage to consume almost half the amount of kerosene consumed by the unconnected ones. Although connection status does not seem to have an effect on the share of household income that is allocated to kerosene purchases, it certainly implies that if we assume all households use kerosene with the same device (e.g., the popular tin lamps), then connected households face less kerosene-based pollution. The results thus support the justification for off-grid rural electrification on the basis that they can lead to reduction or eventual elimination of kerosene use in the household (see Jacobson 2007; Komatsu et al. 2011; Hirmer and Cruickshank 2014). Komatsu et al. (2011) also found that as a result of electrification via SHS in Bangladesh rural villages, 95% of the households eliminated the use of kerosene in their households. Therefore, with interventions such as adoption of re-chargeable torches for power back up and/or enhanced infrastructure that reduces frequency of repairs, it is possible to eliminate use of kerosene in the households utilizing microhydro services in Kenya. Unlike in Khandker et al. (2012), we did not find significant reduction in kerosene spending due to electrification. However, this was not the same for some energy-related spending like charging of mobile phone batteries.

Households that are not connected to microgrids spend approximately 0.92 USD (1 USD is equivalent to Ksh. 100) more per month on recharging their mobile phones batteries, compared to those who are connected to microgrids. The treated households spend almost nothing (this is because their reported mobile expense is below Ksh. 10, which is the minimum price) to charge their mobile phones per week, while those who are not connected spend approximately Ksh. 30 per week for the same. This also means that mobile phone owners who live in non-connected households are more likely to face communication hindrances because of lack of reliable electricity to recharge their devices. If they do not have cash to pay for recharge at some other place, then the inconveniences are even higher. There are similar findings by Komatsu et al. (2011) who found that in Bangladesh, households that had adopted SHS electrification had the ease of charging their mobile phones at home without any extra financial costs.

Finally, school children in households that are connected to microhydroelectricity were found to be devoting lesser time to evening study compared to those who did not have microhydroelectricity connection to their household. While the average study period for those in connected homes is 1.35 h, those in non-connected households study for 2.06 h. This contrasts findings from empirical work in Vietnam by Khandker et al. (2013), but coincides with ethnographic findings in South Africa by Matinga and Annegarn (2013). The latter observes that once electricity is available in the households, children are also likely to take up other activities like TV or Radio entertainment instead of studying. Therefore, at first glance the expectation of increased studying due to electrification may not always be supported in some research contexts.

Conclusion

The main task in this paper was to isolate the impact of rural electrification by the use of microhydro schemes on selected aspects of household welfare identified as follows: kerosene consumption, education, access to communication and information, and availability of extended light hours at night. Observational data was used from connected and unconnected households in Kenya where microhydro projects have been implemented on trial basis. Both kernel and nearest neighbor matching techniques were used, and the quality of matching was assessed, where no bad matches were reported and the results were insensitive to assumptions of the analytical method used. Significant impact of electrification was found for three outcomes namely, monthly consumption of kerosene, the number of evening study hours for kids, and monthly mobile phone recharging expense. Although microhydro service that is currently offered provides limited voltage, they deliver significant improvement in aspects of household welfare. If the service provision is enhanced, they can lead to elimination of kerosene lighting in the household and associated health and safety dangers. Uninterrupted access to powered mobile phone devices and subsequent benefits from the availability of electricity accrue to households because of lower costs (e.g., financial and travel time) of recharging batteries. Availability of electricity may also reduce the time allocated to studies due to take up of entertainment activities. Therefore, it is not entirely true that electrification may lead to increased home study time, which is in turn expected to lead to better education outcomes. Further studies tracking other education outcomes are important for this case, since we did not collect data on the same. We have obtained suggestive evidence that primary energy needs for rural households can be met without having to extend the national grid to these households. This is an important lesson for energy resources conservation as well as efficiency, since grid extension to isolated rural areas is associated with higher system losses. Another interesting aspect for future research would be to compare same outcomes for off-grid and grid-electrified households, given that grid-connected households in developing countries limit electricity use to basic applications that can be fulfilled using off-grid electrification.

Acknowledgments The authors are grateful to the Environment for Development (EfD) for funding the fieldwork for this study, and the enumerators and households in the three counties of the Republic of Kenya that participated in this study. We also acknowledge financial support in preparation of this article from Economic Modelling for Climate-Energy Policy (ECOCEP)

Appendix

Table 1 Outcomes of interest

Outcome	Measurement
Kerosene consumption per month	Liters
Kerosene budget share	Ratio
Kerosene energy budget share	Ratio
Cell phone battery recharge/week	Kenya shilling (Ksh.)
Radio use	Hours the radio is used per day
Kids' evening study time	Hours

Table 2 Differences in the covariates before matching (mean for treated units and less mean for untreated units)

Independent variable	*t*/*z* value
Household size	0.0578
Gender_male	3.4921**
Size of arable land	−2.6584**
Piped water connection	−1.2543
Religion_Protestant	−0.1572
Received environmental training	−3.1565**
Dwelling_non-permanent	4.7468**
Kerosene cost/l (Ksh)	−0.4165
Log income household	−4.2166**
Age of head	−2.6880**
Years of education	−0.9337
Outcome variable	*t*-value
Kerosene consumption per month	5.3828**
Kerosene budget share	2.8313**
Kerosene energy budget share	2.7474**
Night light hours	−0.0711
Cell phone battery recharge/week	4.6211**
Radio use	−0.5691
Kids' evening study time	0.6864

**Significant mean difference at 1%

Table 3 Naïve regression results (regression of the treatment dummy and *X* on the outcomes)

	Share of kerosene expenditure in energy budget	Physical consumption of kerosene in liters per month	Kids' study hours	Mobile phone recharging cost	Night light hours	Share of kerosene expenditure in household monthly budget	Duration of radio use in a household
Treated ($D = 1$)	−0.0628441	−1.458929**	−0.348506	−24.48824**	−0.0901869	−0.0042953	0.1501879
Household size	0.0024549	0.2347184**	0.2932365**	1.767004	−0.035125	−0.0004477	0.1605117
Gender(male)	0.0559232	−0.0521598	−0.2752196	−5.976015	−0.161545	0.0040185	−0.2449557
Arable land	0.0040933	0.0006729	0.0654025	−0.0747607	0.140495	−0.0003605	−0.0627393
Piped water present	−0.0511294	−0.5311659*	−0.1993111	−4.473489	−0.1717192	−0.0076998**	0.1675696
Environmental training (yes)	−0.0793706*	−0.2983379	0.3377692	9.295664*	−0.654048*	−0.0049086*	−0.8645319***
Dwelling (non--permanent)	0.0194716	−0.6170066*	−0.1493446	−6.44442	−0.2781416	−0.0007385	−0.2717329
Monthly income (log)	−0.0311671*	−0.1503291	−0.0361287	−1.024557	0.1158561	−0.0022539***	0.1424919
Age (head)	0.0149566***	−0.011837	0.1087858**	−2.685003**	−0.0533175	−0.0001274	0.0270649
Age(head) squared	−0.0001148	0.0001442	−0.0010401**	0.0217149**	0.0004348	2.43e−06	−0.000144
Number of years in school	0.0005903	−0.0222054	0.0626664**	0.3031101	0.0404713	−3.50e−06	0.1265202*
Religion (protestants)	−0.0385324	−0.0886825	−0.1112844	−4.834935	−0.0537297	−0.0030961	0.3519142
k	0.1482461	4.728612**	−2.097109	113.0504**	3.767615	0.046326**	1.497069

**, *, ***Significant mean difference at 1, 5, and 10% respectively

Table 4 Logit results (treated as the dependent variable)

Variable	Coefficient (SE)
Household size	0.0126(0.0935)
Gender(male)	−1.0504(0.3467)**
Arable land	0.05280(0.0865)
Piped water present	0.0553(0.3773)
Environmental training(yes)	1.1555(0.3766)**
Dwelling(non-permanent)	−1.2965(0.3600)**
Kerosene cost/l (Ksh)	0.0222(0.0152)
Monthly income (log)	0.6445(0.1835)**
Age (head)	−0.0024(0.0724)
Age(head) squared	0.0002(0.0006)
Number of years in school	−0.0206(0.0423)
Religion	0.0665(0.3290)
k	−8.5593(0.2.9985)**
LR chi-square (12)	65.82
n	267

**, *, ***Means significant at 1,5 and 10 %, respectively

Table 5 Impact: kernel (Epanechnikov) results

Outcome variable	(a) Base (bwidth = 0.06)	(b) K (bwidth = 0.04)	(c) K (bwidth = 0.08)
Kerosene demand in liters	−1.4941 (0.3064)**	−1.4680(0.3431)**	−1.4846(0.3209)***
HH budget share of kerosene	−0.0048 (0.0035)	−0.0046(0.0031)	−0.0046(0.0031)
Energy budget share of kerosene	−0.0573(0.0487)	0.056(0.0475)	−0.0585(0.0449)
Night light hours	−0.2629(0.5076)	−0.2803(0.5186)	−0.2705(0.5020)
Cell phone charging expenditure/week	−23.2364(4.6132)**	−23.3831(4.6722)**	−23.6174(4.3087)**
Radio hours	−0.4735(0.7258)	−0.3476(0.6966)	−0.2979(0.6806)
Kids' study hours	−0.7110(0.3289)*	−0.6960(0.3146)*	−0.6622(0.3200)*

**, *, ***Significant mean difference at 1, 5, and 10% respectively (bootstrap standard errors)

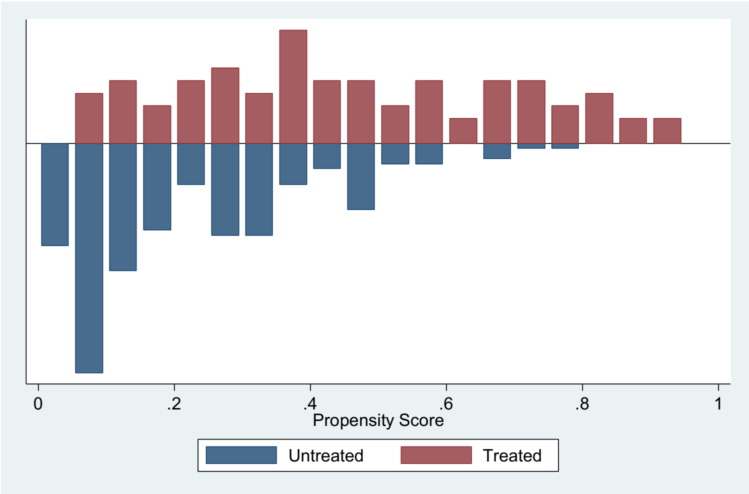

Fig. 1 Propensity score imbalance before matching. The flat line is the zero count for the frequency of units available at each propensity score

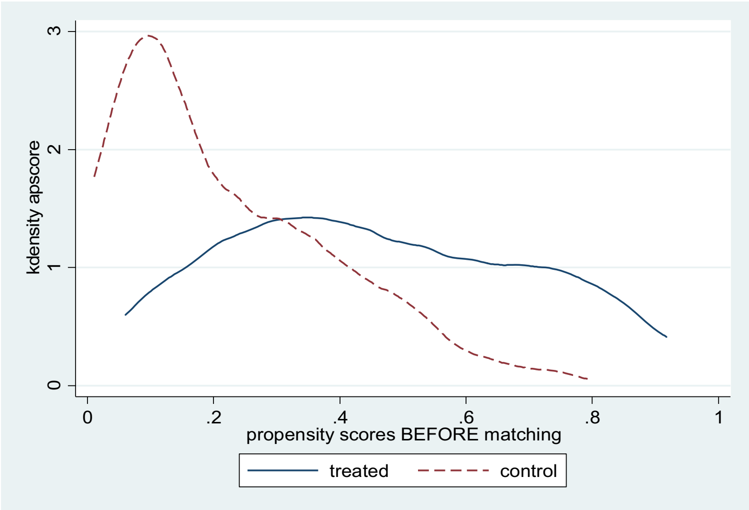

Fig. 2 Distribution of propensity score distribution before matching. Dotted line represents distribution of propensity scores for control units before matching. Solid line represents distribution of propensity scores for treated units before matching

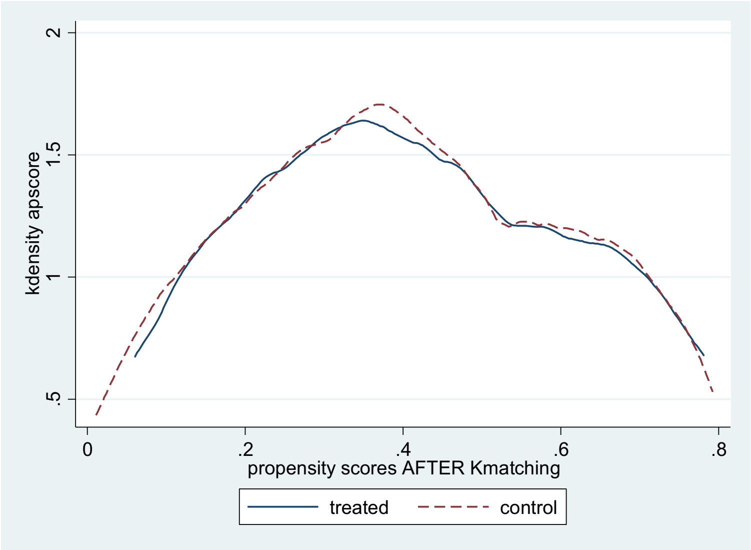

Fig. 3 Distribution of propensity scores after matching. Dotted line represents distribution of propensity scores for control units before matching. Solid line represents distribution of propensity scores for treated units before matching

Table 6 Sensitivity analysis: kernel (Epanechnikov)

Gamma	Sig (+)	Sig (−)	t-hat (+)	t-hat (−)
Kerosene consumption per week				
1	1.2e−07	1.2e−07	−1.7838	−1.7838
1.1	1.7e−08	6.7e−07	−1.8436	−1.7220
1.2	2.5e−09	2.9e−06	−1.8972	−1.6576
1.3	3.7e−10	9.7e−06	−1.9506	−1.5838
1.4	5.4e−11	2.8e−05	−1.9936	−1.5120
1.5	8.0e−12	6.9e−05	−2.0358	−1.4566
Cell phone charging expenditure/week				
1	5.2e−11	5.2e−11	−28.5036	−28.5036
1.1	4.8e−12	4.6e−10	−28.6894	−28.2332
1.2	4.5e−13	2.8e−09	−28.8812	−28.0465
1.3	4.1e−14	1.3e−08	−29.0378	−27.8327
1.4	3.9e−15	4.9e−08	−29.2279	−27.6458
1.5	3.3e−16	1.5e−07	−29.3610	−30.8688
Kids study hours				
1	5.7e−4	5.7e−4	−0.8344	−1.3365
1.1	1.6e−4	1.8e−4	−0.9059	−0.7587
1.2	4.4e−5	4.6e−3	−1.0349	−0.6567
1.3	1.2e−5	0.01	−1.1016	−0.6
1.4	3.2e−06	0.0182	−1.1839	−0.5601
1.5	8.3e−07	0.0768	−1.2477	−0.4930

Gamma-log odds of differential assignment due to unobserved factors Γ

*The lower bound confidence intervals are not reported but show insensitivity of the obtained impacts

Sig(+) upper bound significance level, Sig(−) lower bound significance level, t-hat (+) upper bound Hodges-Lehmann point estimate, t-hat (U−) lower bound Hodges-Lehmann point estimate

Table 7 Impact: nearest neighbor (NN) matching results

Outcome variable	(a) NN (1); $c = 0.25$	(b) NN (2); $c = (0.25)$
Kerosene demand in liters	−1.6089 (0.3989)**	−1.4214(0.3930)**
Household budget share of kerosene	−0.0038(0.0034)	−0.0028(0.0031)
Energy budget share of kerosene	−0.0402(0.0535)	−0.0491(0.0517)
Night light hours	−0.4107(0.5115)	−0.4869(0.4945)
Cell phone charging expenditure/week	−29.0725(7.3445)**	−23.2319(6.7314)**
Radio hours	−0.3051(0.6783)	−0.1435(0.7203)
Kids' study hours	−0.7290(0.3608)**	−0.7971(0.3367)**

Changing the caliper to 0.2 did not make any major difference for the 2 neighbors case

**Significance at 1%

Table 8 Sensitivity analysis: nearest neighbor matching (1); (2) $c = 0.25$ and $c = 0.2$

Gamma	Sig (+)	Sig (−)	t-hat (+)	t-hat (−)
Kerosene consumption per week				
1	9.8e−09	9.8e−09	−1.75	−1.75
1.1	1.2e−09	6.4e−0.8	−1.8333	−1.6964
1.2	1.6e−10	3.1e−07	−1.8975	−1.6146
1.3	2.0e−11	1.2e−06	−1.9583	−1.5531
1.4	2.5e−12	3.7e−06	−2	−1.5
1.5	3.1e−13	9.8e−06	−2.0417	−1.4542
Cell phone charging spending week				
1	2.6e−10	2.6e−10	−25	−25
1.1	2.6e−11	2.0e−09	−25	−25
1.2	2.7e−12	1.1e−08	−27.5	−22.5
1.3	2.8e−13	5.0e−08	−27.5	−22.5
1.4	2.9e−14	1.7e−07	−27.5	−20
1.5	3.3e−16	5.2e−0.7	−30	−20
Kids' study hours				
1	2.6e−4	2.6e−4	−1	−1.5
1.1	6.9e−5	8.9e−4	−1	−0.875
1.2	1.7e−5	0.0024	−1.25	−0.825
1.3	4.4e−06	0.0054	−1.25	−0.75
1.4	1.1e−06	0.011	−1.25	−0.75
1.5	1.1e−06	0.019	−1.375	−0.625

Gamma-log odds of differential assignment due to unobserved factors Γ

*The lower bound confidence intervals are not reported but also show insensitivity of the obtained impacts

Sig (+) upper bound significance level, Sig (−) lower bound significance level, t-hat (+) upper bound Hodges-Lehmann point estimate, t-hat (U−) lower bound Hodges-Lehmann point estimate

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