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Abstract

The use of small-scale off-grid renewable energy for rural electrification is now seen as one sustainable energy solution. The expectations from such small-scale investment include meeting basic household energy needs and thereby improving 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 impacts. This paper uses field data from micro hydro schemes in Kenya and a propensity score matching technique to demonstrate such an impact. We find that, on average, households connected to micro hydroelectricity consume 1.5 litres less kerosene per month compared to households without any such electricity connection. Also, non-connected households spend 0.92 USD more for re-charging their cell phone batteries per month in comparison to those who were using micro hydroelectricity service. Finally, school children from households that are connected to micro hydroelectricity were found to devote 43 minutes less to evening studies compared to those without electricity. The findings provide interesting insights about some of the claims made for or against the use of off-grid renewable energy for rural electrification.

Key Words: Micro hydro, rural electrification, impact, Kenya

JEL Codes: C21, Q01, Q42

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Mary Muthoni Karumba and Edwin Muchapondwa*

1. Introduction

The International Energy Agency estimates that 1.2 billion people in the world had no electricity access as of 2013. 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 programmes 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). The many advantages of microgrids over a national grid include lower energy losses during transportation, since electricity generation occurs near the consumers (Abu-Sharkh et al. 2006). Such systems are also useful means of energy conservation 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 out to determine the impact of rural electrification on several claimed outcomes. The goal of in this paper is to isolate the impact of rural electrification by use of micro hydro schemes on selected aspects of household welfare in

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Kenya; these outcomes are kerosene consumption, education, ease of charging telecommunication devices, availability of extended hours of light at night, and children's hours of study.

Barnes and Binswanger (1986) note that RE projects take a long time to materialize, in addition to the fact that rural households may take a long time to make the connection or adoption decision. Consequently, the socio-economic benefits may take a long time to show up, even if a lot of unrecoverable resources have already been spent. Methodological difficulties in evaluating these projects are apparent in the literature, given that the most suitable methods of establishing impact, such as Randomized Control Trials (RCTs), may not be easily applicable. This is because electrification projects in developing countries are mostly subsidized; in addition, isolating treatment and control groups in electrification of poor households may raise ethical challenges. Despite these difficulties, several attempts have been made to quantify the changes that occur for 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 such as Bensch et al. (2011). Thus, there is no a guarantee that households in all electrified geographical regions will get an income gain attributable to electrification. However, other studies such as 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 lighting (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 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 necessary.

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. However, 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 be able to afford the cost of cooking with electricity.

The obvious point in the literature is that electricity can affect different aspects of human welfare, all of which are important. 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. 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.

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 such as Bensch et al. (2012) may not be very informative about 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 the 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.

1.1. Micro Hydro Electricity 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 to 2003, with the advent of a political regime change. Several changes in the electricity sub-sector culminated in adjustments in the Energy Act and a Sessional Paper on Energy that recommended separation of generation and distribution functions, as well as the introduction of an 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 percent of the rural population having access to electricity.[1]

The use of off-grid renewable energy technologies, such as micro grids 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 (for example, solar home systems or individual micro grids) or communities (micro solar/hydro grids) to either meet their primary energy needs or supplement other energy sources. Community-owned micro hydro grids offer one such alternative; they originated with two demonstration projects set up by the Government of Kenya in conjunction with development partners (United Nations Development Programme and Practical Action) in 2000. Two communities were mobilized to set up micro hydro grids that would later act as technology references for other groups. What followed was a long trial period. Demand for this alternative electrification remains high even in places that have grid presence, but state support for such local electrification projects has been reduced. The reduction in support has not dampened the interest in 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 micro hydro potential, a scheme would be established, and participating households within the radius of the micro hydro 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 labour and financial obligations are eligible for connection of power into the households in several phases. Because of financial or technical limitations, most community micro hydro grids in Kenya are designed to provide basic electricity services to member households, ranging from lighting to powering small appliances such

[1] Based on 2015 World Energy Outlook Database.

as televisions. As a result of this limited use, one would not expect outcomes associated with heavy use of electricity such as cooking or pumping water. An interesting observation is that households connected to the grid in these rural areas limit electricity use to similar lighting uses, due to affordability issues and availability of other cheaper alternatives for cooking. Nevertheless, it is important to isolate the impact of micro grid electrification that has been claimed in the literature, since such impacts inform the investment decision in the first place. This study seeks to establish such impacts using observational data collected from participating and non-participating rural households in established community based micro hydro schemes.

2. Literature Review

Impact evaluation studies for electrification and other infrastructure projects have become popular only 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 mainly use attributions to claim impact and those that put emphasis on addressing endogeneity (participation bias) while seeking causal impact. The first group of studies collect post-electrification data to describe what consumer behaviour looks like after electrification, or to compare outcomes based on whether or not one has electricity. The limitation of these studies is that the claimed benefits, such as extended night activity and clean indoor air, cannot be attributable to electricity access only, since other influences are not controlled in the environment in which the studies are trying to isolate impact. This weakness is addressed by other studies that create an experimental atmosphere or try to mimic one, which permits a claim of causal impact of electrification. Both types of studies are reviewed here.

The most obvious way to tell 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 that this impact is obvious and do not test for its existence. It is not automatic that a household will benefit from increased hours of light if electrification is accompanied by poor service, including frequent or lengthy 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. However, the measure used in Bensch et al. (2011) aggregates the light hours in a day from all sources and does not account for the fact that more light hours from use of, for instance, a tin lamp is a non-desirable outcome due to the associated pollution. The alternative that we explore in this study is capturing increased hours of lighting attributable to clean energy such as electricity, which is a better indicator of improved welfare of households resulting from electrification.

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 two years of electrification in a country with 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 (SHSs) 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 would like to use electricity for activities such as cooking, a combination of cost and 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 accrues 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 labour effort, 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 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 latter 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 the 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 micro enterprises, such as that described by Jacobson (2007) and Kirubi et al. (2009) in Kenya, but income gains may not be realized due to market bottlenecks. Obermaier et al. (2012) advise that, for electrification programmes to be successful, they must be integrated into the greater rural development strategy. Twin objectives of increasing access as well as increasing electricity consumption through other facilitation programmes must be met in addition to simultaneously implementing other non-electrification programmes. These other supporting programmes 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 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, so introduction of electricity may reduce the demand for firewood, subsequently freeing up some of their time. This additional time may be translated into increased labour 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 per cent of rural electricity consumption devoted to lighting and television (see Köhlin 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 this gender-related outcome is farfetched in developing countries.

Results for educational gains from electrification are mixed. Although electricity makes available 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; more often than not, there is no long-term data to indicate whether 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 (such as capital) may lead to higher gains from electrification because such households possess higher ability to pay for other services.

In addition to the above contradictory outcomes from rural electrification, a major concern in empirical work is 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 how well their econometric approaches 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) and 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, making it a feasible approach whenever such data is available. Dinkelman (2011) uses community gradient in a study of communities distributed in South Africa’s province of Kwa Zulu Natal to establish the labour market gains from electrification, while the distance from nearest connectivity point in India is used as an exogenous instrument for electricity access in India (Khandker et al. 2009). In 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, studies that have looked at small-scale electrification (Kirubi et al. 2009; Komatsu et al. 2011) adopt 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, which is popular with grid electrification, is rarely the motivation behind village micro grids, one needs to be conservative with the choice of outcome selection for impact analysis (Matinga and Annegarn 2013).

Overall, the 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, and such 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.

3. Methodology

This section addresses the econometric procedures to deal with endogeneity of household connection to a village micro hydro 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.

3.1. 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 if he/she 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 was not 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 (ATT).[2] This is impossible because the treatment cannot be removed from the subject once given, so an average treatment effect based on the population of interest is used as an approximation as follows:

$$t_{ATT} = E\,(t|D = 1) = E\,[Y\,(1)\,|D = 1] - E[Y\,(0)|D = 1] \tag{2}$$

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 Randomized Controlled Trials (RCTs), using $E\,[Y\,(0)\,|D = 0]$ as an alternative provides valid estimates of treatment effects, 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:

$$E\,[Y\,(1)\,|D = 1] - E\,[Y\,(0)\,|D = 0] = t_{ATT} + E\,[Y\,(0)|D = 1] - E[Y\,(0)|D = 0] \tag{3}$$

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

$$E\,[Y\,(0)\,|D = 1] - E\,[Y\,(0)\,|D = 0] = 0 \tag{4}$$

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

Experimental studies ensure that the difference between the counterfactual terms for treated subjects and the observed outcome for control subjects is zero. 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. These include regression methods, instrumental variables, and propensity score matching-based methods.

Propensity Score Matching (PSM) 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. Because it is a balancing score, 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. 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 mean outcomes of treatment and control subjects at each value of the score yields an 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 than the other two methods highlighted in the previous sub-section.

The first step in carrying out PSM is to estimate the scores using a choice model, in order to 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:

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

where $E_{(Pr(X)|D=1)}$ is the distribution of the subjects' propensity score, which is used as a weight of the difference between the outcome of the treated and untreated subjects within

[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 the 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 region of overlap. The next section explains the link between access to electricity through a micro hydro service and the expected improvements in the welfare of the connected households.

Change Mechanism

The change mechanism is basically what follows after any electrification programme: once a micro hydroelectricity project is taken up by a community, some households join the scheme and subsequently contribute the relevant financial and labour 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 micro hydroelectricity has limited applications at the household level. Therefore, it would be reasonable to expect outcomes that are associated with the use of low voltage items in the household, which comprise mainly lighting and small appliances.

Kerosene is the primary source of lighting in 68.93 per cent of Kenyan households, and the prevalence of kerosene lighting is higher in rural areas than in 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 micro grids have a lower average consumption of kerosene in terms of both the physical quantities and spending. Kenya is a net importer of crude oil products and the fluctuations in the price of these products directly affect households using kerosene as a primary energy source. This is the reason behind the controversial subsidy on kerosene in Kenya, and it would be interesting to establish whether micro grid 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’s 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, ability to use

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

information and communication appliances like radios, televisions and mobile phones is 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 re-charging 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 summarizes the outcomes of interest for this study, and their measurements using the methods described in the next section.

3.2. Empirical Strategy

Data Collection

This exercise involved comparing outcomes of households that are connected to community micro grids to those with no connection to micro hydro scheme electricity service. There was no comprehensive list of micro hydro schemes in Kenya at 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 micro hydro electricity 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 fairly similar conditions. Due to the technical requirements for micro hydro electricity generation, all the 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 similar economic opportunities. The control households were randomly picked from the pool of non-connected households within the defined radius of a micro hydro 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 and 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), and 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 knowledge of the research area, and past research should form the criteria for choosing variables. This study relied on the first two criteria. 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 head}.[5]

The probability that a household is connected to micro hydroelectricity is $E(Y = 1)$, which is a linear function of X as follows:

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

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

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

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

Section 3.1 highlighted that one of the conditions for estimation of ATT is the presence of overlap or a common support region in the data. This will ensure that subjects

[5] Naïve regressions of treatment dummies and their predictors on each outcome were conducted. 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).

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

with the same propensity scores have a chance of either being connected to the micro hydro grid or not. The best way to demonstrate the existence is through visualization using density plots (see Figure 1).

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 scores. As Section 3.1.1 indicated, a propensity score is actually a balancing score. This implies that, within each propensity score stratum, the treated and control subjects should have the same distribution of observed covariates, so that they are comparable. According to Austin (2011), one way of ensuring that the model for estimating the propensity scores is 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 to check for balancing quality after matching (Austin 2011). The use of standardized differences in means seems to be superior and is adopted in this study. The standardized differences in means for a continuous variable are calculated as given below:

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

while that of a binary outcome variable is given as:

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

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

The one thing that is clear in the 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 there are 'bad' matches (see Garrido et al. (2014) and Austin (2011), among others). Other methods, such as the use of t-tests and model fit measures, have been discredited due to the disconnect between their major assumptions and the purpose for which propensity scores are estimated.

Choice of Matching Methods

The general framework for PSM estimator for Average Treatment Effect (ATT) was shown in Section 3.1.1. 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 households to those of the 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 (neighbours); 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 neighbour matching.

Kernel Matching

We 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 the 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 a nearest neighbour estimator, which is inefficient but introduces less bias as a 'robustness' check (see Caliendo and Kopeinig (2008)).

Nearest Neighbour (NN) matching

This estimator involves picking 1 *k* treated and control subjects who have the 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 neighbour may be too distant from its treated counterpart in terms of propensity score (Garrido et al. 2014).

Sensitivity Analysis

From Sub-section 3.1.1., 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 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 micro hydro service θ. Rosenbaum (2002) relates the odds ratio of two such households to a parameter Γ representing the effect of the observable characteristics on the selection into connection decision as follows:

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

For the classical case of randomization, this parameter takes the value of 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 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 the 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 γ = 0 (that is, no 'hidden bias). Insensitive results imply that a very big γ is required to alter the base inference.

4. Results

4.1. Data Description

The treated and control subjects are similar in only 5 out of 10 characteristics (see Table 2). 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 is also shown in Table 2.

4.2. Propensity Score Estimation Model

From Table 4, having a male household head and a non-permanent living structure is associated with a lower probability of being connected to a micro hydro grid service. 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 in 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 Figure 2. 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 whether 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 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 neighbours 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.

4.3. Treatment Effect Using Kernel Matching

Significant effects of electrification through micro grids were found on 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. Treated households reported lower average consumption of kerosene per month compared to untreated households, which is a desirable outcome. Further, connected households spent less money on recharging mobile phone batteries compared to those that were not connected, which also is a desirable outcome. Children in connected households spent less time studying in the evening compared to their counterparts in households without any electricity connection. This is not a desirable outcome on its own since it has been expected that children would prolong their evening study period due to availability of a convenient source of lighting. There is no significant difference in either the hours of light at night or radio entertainment between connected and non-connected households. The results were robust to changes in bandwidth changes as well as to use of nearest neighbour matching with several calipers. No bad matches were reported by the standardized difference of means ratios. The sensitivity analysis was implemented using a code provided by Gangl et al. (2004). The implication from this test is that the impacts obtained are insensitive to changes in the assumption we made on unconfoundedness (see results in Tables 6 and 8). Therefore, matching gives us a fair indication of what is happening in the sample.

We now offer a contextual interpretation of the significantly different outcomes. While households which are not connected to the micro grid consume about 2.8 litres of kerosene per month, the connected households consume about 1.3 litres, resulting in a difference of approximately 1.5, which is reported in Column (a) in Table 5. The explanation for the 1.3 litres of kerosene consumed by the connected households is due to frequent repairs or breakdowns that were reported in most electricity generation 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, these findings imply 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 it 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 Solar Home Systems in Bangladesh rural villages, 95 per cent 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 breakdowns, it is possible to eliminate the use of kerosene in households utilizing micro hydro services in Kenya. Unlike Khandker et al. (2012), we did not find significant reduction in kerosene spending due to electrification. However, there was a reduction in spending on recharging mobile phone batteries.

Households that are not connected to micro grids spend approximately 0.92 USD (1 USD is equivalent to Ksh. 100) more per month on recharging their mobile phone batteries, compared to those who are connected to micro grids. The treated households spend almost nothing to charge their mobile phones per week (this is because their reported mobile expense is below Ksh. 10, which is the minimum price), 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 greater. There are similar findings by Komatsu et al. (2011), who found that, in Bangladesh, households that had adopted Solar Home Systems 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 micro hydroelectricity were found to be devoting less time to evening study compared to those who did not have a micro hydroelectricity connection to their household. While the average study period for those in connected homes is 1.35 hours, those in non-connected households study for 2.06 hours. 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 such as 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.

5. Conclusion

The main task in this paper was to isolate the impact of rural electrification by use of micro hydro schemes on selected aspects of household welfare: 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 micro hydro projects have been implemented on trial basis. Both kernel and nearest neighbour matching techniques were used, and the quality of matching assessed; no bad matches were reported and the results were insensitive to assumptions of the analytical method used. Connection to micro hydroelectricity led to decreases in kerosene consumption and mobile battery recharging expenses, both of which are desirable outcomes. On the other hand, the study duration for children in connected households declined, which is an undesirable outcome. Although micro hydro service that is currently offered provides limited voltage, it delivers significant improvement in aspects of household welfare. If the service provision is enhanced, this can lead to reduction 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. However, availability of electricity may reduce the time allocated to studies due to take-up of entertainment activities. Therefore, it is not clear 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 the same outcomes for off-grid and grid electrified households, given that grid connected households in developing countries generally limit their electricity use to basic applications that could be fulfilled using off-grid electrification.

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Tables

Table 1. Outcomes of Interest

Outcome	Measurement
Kerosene consumption per month	litres
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	hrs

Table 2. Differences in the Covariates before Matching (Mean for Treated Units 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/litre (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

**indicate 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 litres 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***	*-.348506*	*-24.48824***	*-.0901869*	*-.0042953*	*.1501879*
household size	0.0024549	.2347184**	.2932365**	1.767004	-.035125	-.0004477	.1605117
Gender(male)	0.0559232	-.0521598	-.2752196	-5.976015	-.161545	.0040185	-.2449557
Arable land	0.0040933	.0006729	.0654025	-.0747607	.140495	-.0003605	-.0627393
Piped water present	-0.0511294	-.5311659*	-.1993111	-4.473489	-.1717192	-.0076998**	.1675696
environmental training(yes)	-0.0793706*	-.2983379	.3377692	9.295664*	-.654048*	-.0049086*	-.8645319***
dwelling(non-permanent)	0.0194716	-.6170066*	-.1493446	-6.44442	-.2781416	-.0007385	-.2717329
monthly income (log)	-0.0311671*	-.1503291	-.0361287	-1.024557	.1158561	-.0022539***	.1424919
age (head)	0.0149566***	-.011837	.1087858**	-2.685003**	-.0533175	-.0001274	.0270649
age(head) squared	-0.0001148	.0001442	-.0010401**	.0217149**	.0004348	2.43e-06	-.000144
no of years in school	0.0005903	-.0222054	.0626664**	.3031101	.0404713	-3.50e-06	.1265202*
Religion (Protestant)	-0.0385324	-.0886825	-.1112844	-4.834935	-.0537297	-.0030961	.3519142
k	.1482461	4.728612**	-2.097109	113.0504**	3.767615	.046326**	1.497069

** , *, ***indicate significant mean difference at 1%, 5% and 10 % respectively.

Table 4. Logit Results (Treated as the Dependent Variable)

Variable	Coefficient (S.E)
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/litre (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)
no 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

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 litres	-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/wk	-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)*

** , *, ***indicate significant mean difference at 1%, 5% and 10 % respectively; (bootstrap standard errors).

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

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

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

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 litres	-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)**

** denotes significance at 1%

__Changing the caliper to 0.2 did not make any major difference for the two neighbours' case.

Table 8. Senstivity Analysis: Nearest Neighbour 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

Sig (+) - upper bound significance level

Sig (-) - lower bound significance level

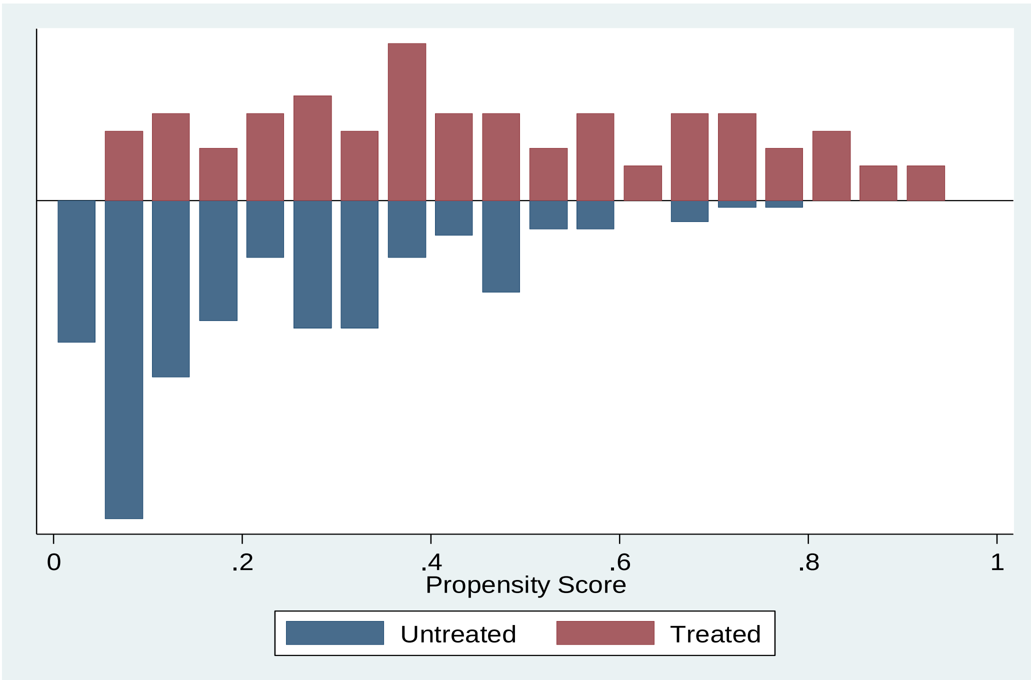
t-hat (+) - upper bound Hodges-Lehmann point estimate

t-hat (U-) - lower bound Hodges-Lehmann point estimate

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

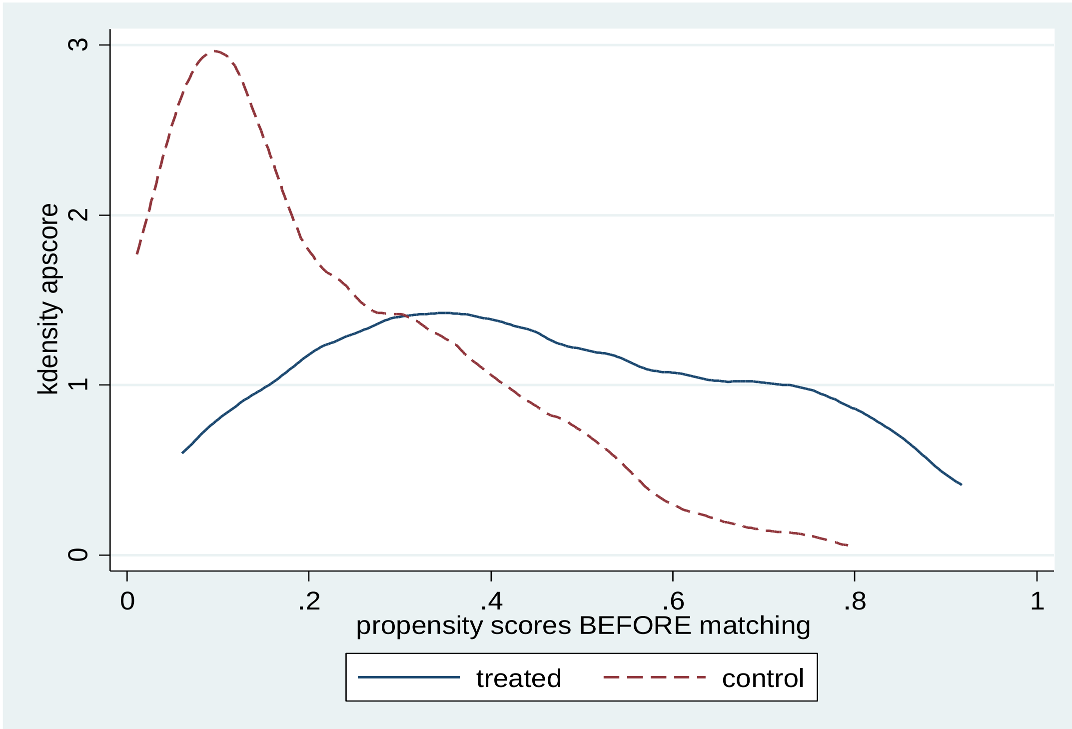
Figures

Figure 1. Propensity Score Imbalance before Matching



The flat line is the zero count for the frequency of units available at each propensity score.

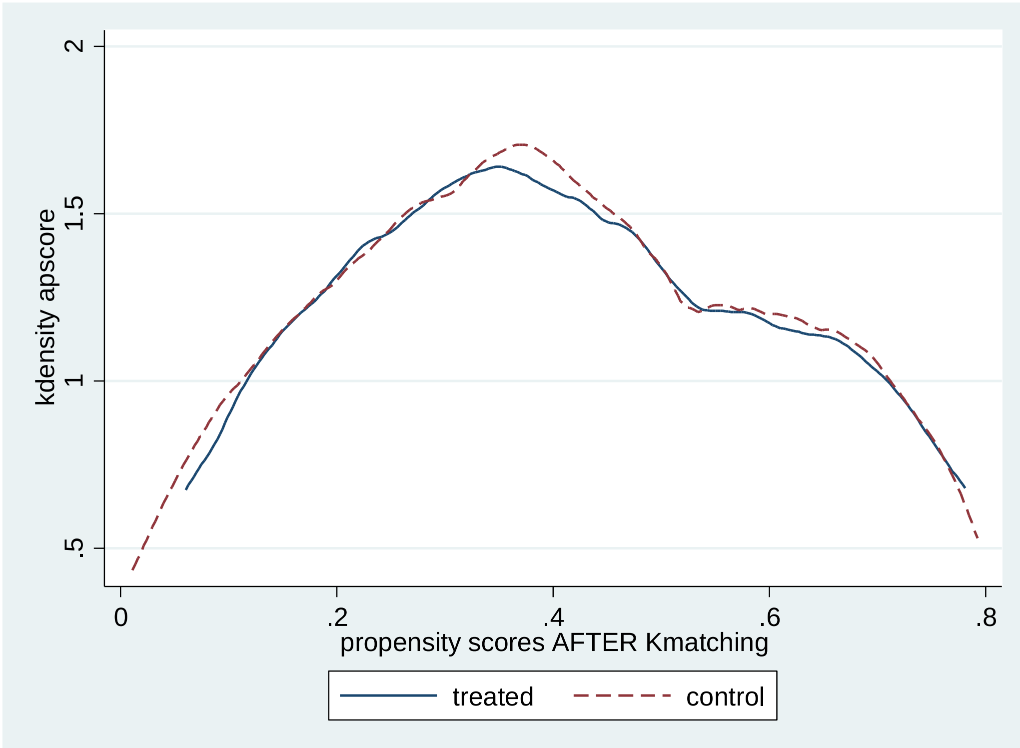
Figure 2. Distribution of Propensity Score Distribution before Matching



Dotted line represents distribution of propensity scores for control units before matching.

Solid line represents distribution of propensity scores for treated unites before matching.

Figure 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 unites before matching.