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Rural Electrification in Rwanda – An Impact Assessment Using Matching Techniques

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Rural Electrification in Rwanda – An Impact Assessment Using Matching Techniques

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Gunther Bensch, Jochen Kluve, and Jörg Peters¹

Rural Electrification in Rwanda – An Impact Assessment Using Matching Techniques

Abstract

Rural electrification is believed to contribute to the achievement of the Millennium Development Goals (MDGs) via various channels. In this paper, we investigate the impacts of electrification on the household's lighting usage, home studying, energy expenditures and income. We use household data that we collected in rural Rwanda in villages with and without access to mini-grids. To account for self-selection processes in the connection decision we use households from the electrified villages to estimate the probability to connect for all households – including those in the non-electrified villages. Based on these propensity scores we identify counterfactual households to determine the impacts of electrification on the outcome indicators. We find some indication for positive effects on home studying and income, but particularly on lighting usage. We conclude by highlighting the potentially profound changes in social life of rural people induced by improved lighting and call for research on impacts beyond the MDGs.

JEL Classification: O12, O13, O18, O22

Keywords: Rural electrification; ex-ante impact assessment; poverty; matching

December 2010

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1. Introduction

Electrification is widely believed to contribute to the achievement of the Millennium Development Goals (MDGs), based on the assumption that sustainable access to modern energy services fosters economic and social development, and leads to improvements in the quality of life. Yet, particularly in rural Sub-Saharan Africa electrification rates are still low, as only 11 % of the population use electricity. In rural Rwanda, the electrification rate is even considerably lower at 1.3 % (UNDP/WHO 2009). As part of the efforts to achieve the MDGs it is among the national policy priorities of most countries to improve access to electricity – be it via extension of the national grid or decentralized electricity. The national target for Rwanda, for example, is to augment the overall electrification rate to 30 % by 2020 – six times the rate in 2005. The international donor community joins these efforts and has increased its support to the energy sector in general and electrification projects in particular (IEG 2008). As part of these international endeavours, the Dutch-German Energy Partnership *Energising Development* (EnDev) envisages the sustainable provision of access to modern energy for 6.1 million people in 17 developing countries. For this purpose, *EnDev*, which is implemented by Deutsche Gesellschaft für Technische Zusammenarbeit (German technical cooperation, GTZ), supports the development of solar and hydro power schemes, biogas and electricity grid extension and densification as well as the dissemination of improved cooking stoves (GTZ 2010).

Against this background of increasing interest in rural electrification, it is crucial to obtain a more solid basis of empirical knowledge about its relevance to different dimensions of poverty. While ESMAP (2003), KHANDKER ET AL. (2009a), and KHANDKER ET AL. (2009b), for example, provide evidence on poverty impacts induced by electrification programmes in Asian countries, empirical

findings hardly exist for Africa.¹ The *EnDev* programme in particular has dedicated itself to monitor outcomes, that is, the number of connected people, and to evaluate the socio-economic impacts induced by the electricity access. Therefore, a couple of target region surveys have been conducted under the *EnDev* umbrella. For the analysis in this paper we use household data collected for the *EnDev* rural electrification project implemented in Rwanda, called *Private Sector Participation in Micro-hydro Power Supply for Rural Development* (PSP Hydro). The survey mainly serves two goals: First, to provide baseline data to be used in an ex-post evaluation of impacts. Second, to assess *before* project implementation the impacts that can be expected from the installation of the micro-hydro mini-grids. For this purpose, not only households in the yet non-electrified project areas were surveyed, but also households in comparable non-project regions that already have access to electricity.

This paper pursues the second goal of assessing the impacts of rural electrification by comparing households in the electrified and non-electrified regions.² The outcomes we consider are lighting usage, children's study time at home, energy expenditures and income. To identify impacts on these outcomes, we first use the information of both connected and non-connected households in already electrified villages only to estimate a probit model with the connection status of households as dependent variable. The estimated model is then employed to predict probabilities to connect for all households in the sample, including those from the yet non-electrified project villages. We then use these probabilities to identify counterfactual households using different

¹ IEG (2008) as one of the few exceptions provides some evidence for Ghana. PETERS AND VANCE (2011) analyze the effect of electrification on fertility in Côte d'Ivoire. PETERS, VANCE, AND HARSZDORFF (2011) and NEELSEN AND PETERS (2011) examine the usage of electricity and its impacts in micro-enterprises.

² Note that the paper does not evaluate the GTZ intervention, although it uses data collected for this project. The evaluation is still underway, as the intervention is being rolled out.

matching algorithms. First, we stratify the households in the non-electrified villages into those that are likely to connect and those that are not. We refer to the former as hypothetically connected and compare them to the actually connected in the electrified villages. In addition, two classical matching approaches, nearest neighbour and Kernel, are used to further verify the results.

The remainder of the paper is organized as follows. Section 2 presents the country background and the *PSP Hydro* project. Section 3 focuses on the design of the underlying survey and gives a first descriptive analysis on the surveyed sites and potential electrification impacts. The fourth section presents the impact analysis using different propensity score matching algorithms. Section 5 concludes.

2. Country and project background

Rwanda is a country located at the heart of the African continent, with a current (2010) population of about 10.5 million people. Given its small territorial size, Rwanda is the most densely populated country in continental Africa. It is a rural country with approximately 90 per cent of the population engaged in agriculture, mainly subsistence farming. Rwanda has few natural resources and its main exports are coffee and tea. Even though the current annual GDP per capita reaches only around USD 900, the country – averaging growth rates of 4.9 per cent per annum since 2000 – has made substantial progress over recent years in stabilizing and rehabilitating the economy to pre-genocide, i.e. pre-1994, levels.

In its "Vision 2020", the government has set a framework of key policies for Rwanda's development based on good governance and leapfrogging. Progress has also been observed in areas such as access to education and health as well as gender equality. Rwanda's achievements in

establishing an aid coordination, harmonization, and alignment framework are being recognized as international best-practice. The latest specific Rwanda National Human Development Report (UNDP 2007) points out that agriculture, demography and income distribution pose major problems on a sustained growth path. Moreover, Rwanda, like the majority of Sub-Saharan Countries, faces a serious lack of electricity supply, which is part of a general energy shortage.

While around 25 % of Rwandan urban households are connected to the electricity grid, only 1.3 % have access to some form of electricity in rural areas (UNDP/WHO 2009). The per capita electricity consumption is one of the lowest in the world and concentrated in the main cities: The capital Kigali alone accounts for more than 70 % of the total national low-voltage electricity consumption. Investments in new generation or network capacities have been very limited in the past, such that energy sector reform advanced only slowly. Apart from imports from neighbouring countries, supply mainly consists of outdated hydroelectric power stations, thermal power stations acquired in 2004 making up as much as half the available national electricity generation of 71 MW in 2010 (MININFRA 2010). Before 1994, less than 20 micro-hydro power plants existed with capacities of around 50 to 100 kW. In 2008, only one of them was operational (SHER 2008). Adding to these supply constraints, the hilly and land-locked character of the country makes the provision of energy to rural areas difficult and expensive.

The Government of Rwanda defined several objectives and targets in order to tackle the persistent problem of rural energy poverty in the country, including increased access to grid electricity (MINECOFIN 2000). As a consequence, a variety of activities in cooperation with the international community has addressed these problems. Most recently, the *Electricity Access Roll Out Programme*, financed predominantly by the World Bank and the Netherlands, has the objective to attain a

national electrification rate of 16 % by 2012. As regards electricity generation, the exploitation of large methane gas deposits in Lake Kivu has recently started. The extraction is technically challenging, but has potentials to multiply installed generation capacity in the country and even allow for electricity exports.

Compared to these large programs, the *PSP Hydro* project is a small-scale effort to tackle energy poverty. Being implemented by GTZ since mid 2006, it is one of the earlier interventions in the sector. In light of a formerly inexistent private electricity generation sector and favourable geographic and climatic conditions for micro-hydro power in the country, *PSP Hydro* aims at developing a private sector for micro-hydro based power generation. The electricity shall either be fed into mini-grids at the village level or into the national electricity grid. For this purpose, subsequent to a tendering process five private Rwandan entrepreneurs have been supported financially and technically in setting up business plans for the investment in the power plants and mini-grids, as well as their installation and operation. The project is part of the Dutch-German Energy Partnership *Energising Development (EnDev)* with ongoing interventions in 17 countries. By 2012, *EnDev* aims at providing 6.1 million people in developing countries with sustainable access to improved cooking technologies, biogas and electricity – be it via extension of the national grids, solar panels, or mini-grids. The innovative feature of *EnDev* is its clear outcome and impact orientation: All projects are obliged to report regularly the number of newly served people and to monitor impacts (GTZ 2010).

3. Research design and data base

3.1 Survey design and implementation

We collected the household data used in this paper during the preparation phase of the *PSP Hydro* project. In designing the survey we took two main purposes into account: First, to provide for

baseline data to be used in an ex-post evaluation of impacts. Second, to assess *before* project implementation the impacts that can be expected from the installation of the micro-hydro mini-grids.³ In order to fulfil the second purpose, we did not only survey the yet non-electrified regions that will be served by the *PSP Hydro* mini-grids, but we also surveyed comparable, already electrified villages.

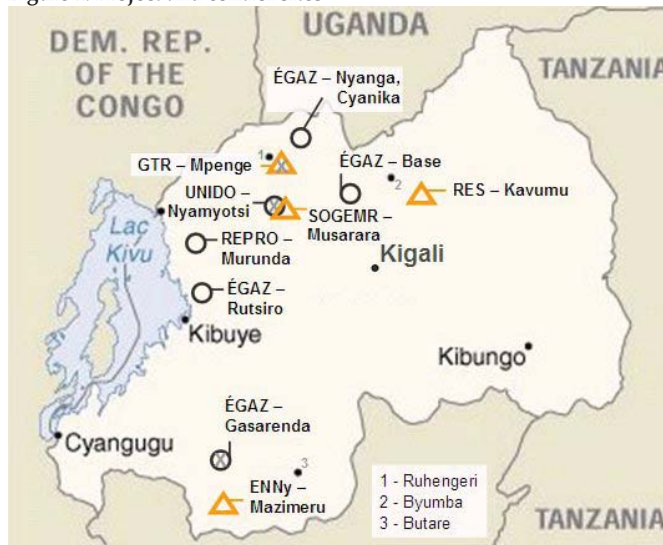
One crucial precondition in this survey set-up is that the two regions – the yet non-electrified project regions and the already electrified comparison regions – are sufficiently similar in their basic socio-economic conditions and business opportunities. To this end, we determined key comparability criteria to choose the comparison regions: the geographical location and distance to the capital Kigali, the rural agricultural structure and cash crop economy, frequency of and distance to local and regional markets, and access to tarmac roads. The electrified villages should furthermore have disposed of electricity access for at least four years. Additional criteria were that the electricity provider should not, for example owing to limited power available, preclude claims of households interested in getting connected or prohibit the use of energy-intensive appliances and machines, e.g. electric irons or mills. Finally, metered billing should be in place in order not to have unmetered, "flat rate" clients distort the data on electricity consumption patterns.

In total, ten sites were surveyed in 2007 and 2008, each site comprising four to ten agglomerations within an area of roughly 15 to 30 sq km (cf. Figure 1). One of the authors worked on the ground during the whole survey cycle in close cooperation with a local Rwandan NGO. Three out of these

³ Additionally, the collected information should serve to verify assumptions in the business plans of the project developers about connection rates and loads – important parameters determining the dimension of the power plants and the grids. The private project developers – small local enterprises and cooperatives – did not have much expertise in the realization of micro-hydro plants and mini-grids. For more information on the overall evaluation scheme of *PSP Hydro*, cf. BENSCH AND PETERS (2010).

ten sites, however, do not entirely fulfil the above mentioned comparability criteria and were excluded from the analysis in this paper.⁴ Altogether, 544 households were interviewed in the seven sites using structured questionnaires; 269 in non-electrified regions and 273 in the electrified regions. Among the latter, 129 households were found to be connected to the grid at the time of the survey. To complement these quantitative data with qualitative information, key informants like local chiefs, NGOs, or project staff were visited for semi-structured interviews.

Figure 1: Project and control sites



Red triangles represent PSP Hydro sites that are not yet electrified, but will be over the coming years. Blue circles are sites already provided with electricity. The REPRO site at Murunda actually is a PSP Hydro site as well, but it already disposed of electricity access before the intervention.

⁴ These three sites were initially included in the survey for reasons related to the *PSP Hydro* project implementation. We exclude the sites of Mpenge and Gasarenda, since they are peri-urban and, hence, non-comparable. The Nyamyotsi site is excluded since electricity consumption is not metered. Households pay a low flat rate and consumption is only limited by the capacity of the local micro hydro plant. The future PSP Hydro customers, in contrast, will have to pay per kWh, thus rendering a comparison difficult.

3.2 Socio-economic conditions in the surveyed regions

In this section we provide information based on the survey that describes the composition and socio-economic characteristics of the households (see Table 1). All project and comparison sites are located in the middle longitudinal corridor of Rwanda. They exhibit comparable geographical and climatic characteristics, e.g. concerning rainfall and topography, the two decisive characteristics for micro hydro power. Although Rwanda is densely populated, people in rural areas live much dispersed on hilly terrain. This dispersion was traditionally bolstered by rules that forbade changing residence without government approval. This is also one reason for the relatively low incidence of migration. Only 13 percent of the surveyed households, for instance, report that any household member has ever been migrating⁵.

The genocide in 1994 that devastated the country's human, physical and social capital was followed by a long, difficult but promising process of recovery. Nevertheless, consequences are still evident – for example in the fact that 25 percent of surveyed households lack either the father or the mother. This is also the reason why 22 percent of the households are headed by a female (Table 1). Almost half the survey population is younger than 15 years. Family sizes are in general relatively small with an average of 5.4 household members. Subsistence farming is ubiquitous: 84 percent of households do possess fields.

Moreover, Table 1 provides descriptive statistics grouping the households into those living in an electrified village and those that live in a non-electrified one, i.e. “access” and “non-access” sites, respectively. The terminology of an “access site” refers to the fact that being an electrified village implies that access to electricity exists in the village, and in principle can be used by everyone

⁵ Household members who left the household due to marriages are not considered in this figure.

living in the village. The decision to actually connect to the electricity grid existent in the village is then made at the household level. The left panel of Table 1 therefore looks at the surveyed households in the villages with access, distinguishing between households that did connect and households that did not. Clearly, households in non-access villages cannot be connected to the electricity grid.⁶

Table 1: Descriptive statistics on survey population, differentiated by electricity access and connection status

	Total	Access villages		Non-access villages	t
		connected	non-connected		
N households	272			265	
N connected		129		6	
N not connected			143	259	
Household variables:					
HH Size	5.2	5.5	4.9	5.6	2.08
Female household head	0.22	0.16	0.27	0.19	0.79
Education years father	8.2	9.8	6.7	5.9	5.53
Education years mother	6.5	8.5	4.8	4.5	5.69
Any HH member migrated	0.17	0.13	0.20	0.13	1.14
Housing variables:					
Household owns the house	0.84	0.84	0.85	0.92	2.88
Floors are cemented	0.49	0.78	0.22	0.33	3.75
Stone or brick wall	0.33	0.55	0.12	0.12	6.12
Glass window	0.52	0.77	0.22	0.23	7.18
Ownership of fields	0.79	0.78	0.81	0.89	3.24
Employment variables:					
HH head subsistence farmer	0.42	0.28	0.54	0.65	5.53
Father occupied in public service	0.26	0.38	0.13	0.13	3.19
Mother occupied in public service	0.17	0.34	0.02	0.06	4.09
Financial variables:					
Bank account ownership	59.2	79.7	41.0	41.5	3.74
Household ever took out a loan	0.33	0.48	0.20	0.29	0.91

Note: N refers to the respective population size and |t| to the absolute value of the t-statistic for test on difference in means between parameter values in access compared to non-access villages.

⁶ Table 1 shows that a total of 6 households in non-access villages reported to be “connected”. In fact, these six households already dispose of an electricity source in the form of an individual generator. For the sake of consistency, they are excluded from the summary statistics presented in the table.

In Table 1 it can also be assessed to what extent the comparability of village level characteristics described above translates into comparability at the household level. Although the comparison sites have been carefully chosen, the table suggests that access and non-access sites do not seem to be fully comparable in the aggregate. The t-statistic values presented in the table (column 5) show that the tests for differences-in-means between the 272 access villages (column 1) and the 259 non-access villages (column 4) are significant for most of the characteristics. However, at least part of the observed differences may be induced by the electrification access. In a first crude analytical step, we therefore additionally account for the heterogeneity between connected and non-connected households. The respective values that are also given in the table (column 2 and 3) indicate that most of the observed differences between access and non-access sites seem to be driven by connected households. Yet, at this stage, it cannot be determined how much of these differences stem from selection processes within the access villages and how much the electrification intervention contributed to these differences. We will scrutinize this question in the following impact assessment section.

Connected households have disposed of their electricity connection for an average of 5.5 years, with a median of three years. The median price they paid for the connection including in-house installations amounted to 110,000 FRw (200 USD). For 91 percent of them, lighting is considered as the main advantage of electricity. Households traditionally use so-called *agatadowas*, traditional kerosene lamps made of used tins, and hurricane lanterns. Candles rather act as a backup lighting source in connected households in case of power outages. Torches are not frequently used either, since people only rarely leave their home after night has fallen. Connected households, on the other side, use fluorescent tubes, incandescent light bulbs and energy saving compact fluorescent

light bulbs on average to the same extent (per household 0.5 of each on average), while the latter two are more popular for in-house lighting. On average 2 to 2.5 bulbs light the households that mainly consist of a single building with different chambers. The use of energy saving bulbs has been strongly supported by the government in recent years and has increased since the implementation of the surveys to the detriment of incandescent light bulbs.

Among the connected households, 8 percent developed any novel activity potentially in need of electricity, such as commerce, milling, welding or sewing. Sewing, a typical home business activity, however, primarily remains an activity that is mechanically powered – even in electrified regions. Only eleven households at all own a sewing machine. Concerning other electrical appliances, only radios and mobile phones can be found in the majority of households in electrified villages. Television sets are present in less than 27 percent of connected households. Yet, more than every second connected household uses electrical appliances beyond lighting, radios and mobile phones. In the non-electrified villages, hardly any electrical appliance is used.

4. Impact Assessment

4.1 Research questions and indicators

The conceptual framework underlying this research is straightforward and in principle based on the results chain⁷ of many electrification interventions: Electricity is newly provided to a region and a certain share of households gets connected to the grid, which is translated into poverty reduction via different channels. While for those households that make use of electricity this might

⁷ The *theory of change* of a development project is typically represented in a results chain that links the intervention's inputs and activities to its outputs and impacts.

happen directly, also the non-connected might benefit from spillover effects or improved social services. DfID (2002) and UN (2005), for example, establish linkages between electricity and most MDGs. Not all of these hypotheses can be investigated with the household level data we have at hand.

In this paper, we focus on impacts on the directly connected households. Four indicators are examined: (i) lighting hours, (ii) time that children use lighting for studying at home, (iii) energy expenditures per household member, and (iv) income per working-age household member. The rationale behind these indicators is as follows: As many impacts related to electrification are based on the usage of modern lighting, *lighting hours* is the first outcome that we examine. While most electrification experts and practitioners might consider this as a trivial question and take effects on this indicator for granted, from an evaluative point of view it is worth verifying if the service is actually taken up: This take up is a necessary condition for many MDG relevant impacts, as they relate to the increased usage of lighting. Furthermore, going beyond the narrow view on the MDG, cheap access to high quality lighting constitutes a major change in the life of rural households with potential long-term effects on many economic and social dimensions.⁸ Without being able to investigate this potential transition in all aspects, we dedicate some effort to scrutinize the intermediate indicator of lighting usage. *Lighting hours* are measured by summing up the amount of light consumed per day over all lighting devices.⁹

In a second step, we use the *kids studying at home* indicator as an intermediate measure to approximate the transmission channel to ultimate educational impacts. We analyze the daily home

⁸ See FOUQUET AND PEARSON (2006) for considerations on the long-term psychological effects of improved artificial lighting usage.

⁹ This indicator thereby is a conservative one, since we do not account for the improved lighting quality. This could also be done by summing up the lumen hours consumed.

studying time of primary school children only, since secondary education in Rwanda is commonly provided at boarding schools.

Third, in order to examine the extent to which electricity usage has materialized already in monetary terms, we look at *energy expenditures* as an indicator for increased disposable income after having paid the energy bill. Electricity is much more efficient as an energy source and, hence, cost savings are likely. On the other hand, one might expect increasing energy usage due to new appliances like television or increased lighting usage. Therefore, we inspect to what extent households effectively save money. In order to account for different household sizes and compositions, we standardize our energy expenditures values by dividing them by the number of “adult equivalents” in the household.¹⁰

The fourth indicator, *income*, is investigated in order to check if improved electricity usage leads to productive usages. In this case, we standardize the indicator by relating it to the number of working-age adults in the household.¹¹

Descriptive statistics on these selected indicators are depicted in Table 2. The observation made for the socio-economic and demographic characteristics presented in the previous section holds for these variables as well: While differences between access and non-access villages are pronounced, these seem to be driven mainly by the connected households.

¹⁰ The scale used to determine adult equivalents is a country specific one and has as well been used, for example, for the National Integrated Household Living Conditions Survey (*Enquête Intégrale sur les Conditions de Vie des Ménages*). See MCKAY AND GREENWELL (2007).

¹¹ Both expenditures and income are expressed in terms of the local currency, Rwandan Francs (FRw), with a per US dollar exchange rate of 568.75 in 2009, 550 in 2008, and 585 in 2007.

Table 2: Descriptive statistics of indicators concerning potential electrification impacts

	total	Access villages		Non-access villages	t
		connected	non-connected	non-connected	
N	272	129	143	259	
Lighting hours per day	13.2	24.5	2.9	3.6	8.02
Lumen hours per day	8,865	18,630	57	63	9.40
Kids studying home (in hours)	0.84	1.12	0.56	0.69	1.53
Energy expenditures per adult equivalent	1610	2190	1150	790	4.57
Income per work-age adult	366,600	562,500	196,800	162,300	4.31

4.2 Identification strategy

From an impact evaluation perspective, our survey design serves to identify the impacts of the treatment *electrification* via two principal strategies. The first and obvious one is the comparison of household indicators before and after the electrification. For this purpose, the data collected in the *PSP Hydro* project villages serves as a baseline that needs to be complemented by a follow up survey capturing the socio-economic conditions after the electrification intervention. The second strategy is what we refer to as *ex-ante impact assessment*: By comparing households in the already electrified non-project regions (*access regions*) to those in the yet non-electrified project villages (*non-access regions*), impacts of electrification can be evaluated using cross-sectional methods. The results of this second strategy are presented in this paper.

In doing so, it has to be taken into account that service interventions in general are difficult to evaluate, since simply comparing outcomes of participants and non-participants may suffer from substantial biases due to selection processes (see FRONDEL AND SCHMIDT 2005; RAVALLION 2008).

As elaborated in PETERS (2009), this applies as well to the case of electrification interventions, where it is the choice of the individual household whether it connects to the grid or not. Households that decide to connect may do so for reasons that are potentially unobservable to the researcher and that, at the same time, affect the outcomes of interest. Such self-selection effects can be expected to substantially bias a cross-sectional impact evaluation that simply compares connected to non-connected households in the access region. In particular, using such a cross-sectional comparison, impacts on income as a major poverty indicator can hardly be evaluated. The reason is that households with higher income are more likely to raise the funds for connecting to the grid. This simultaneity of income and connection status implies that it cannot be disentangled if a household has a higher income because it is connected, or if it is connected because it has a higher income (see PETERS 2009).

To address these *selection-into-treatment* processes, we use the household data from both the access and the non-access regions: This survey set-up enables the comparison of connected households from the already electrified access region to *comparable* households from the non-electrified non-access region. That is, we use the information from the access villages on which types of household did connect and which types did not to identify among all households in the non-access villages those that are most likely to connect once access is provided. By thus including households from the non-access region we increase the probability of identifying the right counterfactual: households in the non-access region that properly resemble the connected households of the access region in every aspect but the fact that they have not received the intervention. Those households have not had the opportunity to self-select into the treatment. Thereby, selection and simultaneity biases can be eliminated to an arguably large extent. The fact that these households are located in

non-access regions also guarantees that they have not benefited from spillover effects. If comparison households are selected from the same villages in which also the electrified households are located, such spillover effects – if they exist – would lead to an underestimation of impacts.

We implement this identification of comparable households by, firstly, estimating a probit model using observations from the access region only. The probit model regresses the connection status of a household on a number of covariates. Including households from the non-access region here does not make sense, since households in this region do not have the possibility to get connected. Instead, secondly, the coefficients from this probit model are used to predict the probability to get connected for each household in both the access and non-access region. These *propensity scores* are then used in the third step to implement different *matching approaches*, i.e. to determine a set of non-connected households from the non-access region that is matched to connected households such that two balanced and thereby equivalent groups are constructed. Electrification impacts can then be measured using differences in outcomes between the two groups.

The covariates to be included in the probit model have to fulfil some conditions: First, matching builds on the so-called *conditional independence assumption* (CIA): The outcome variables must be independent of the treatment (in our case grid connection of the household) conditional on the propensity score, i.e. the observed covariates. This assumption requires that the covariates are *non-responsive* to the connection status (ROSENBAUM 1984; HARDING 2003). Furthermore, only covariates should be included that affect both the decision to connect and the outcome variable (SCHMIDT AND AUGURZKY 2001; CALIENDO AND KOPEINIG 2005). In the optimal case, one has pre-intervention observations at hand, for example household income at the time of the grid connection. Lacking these, we utilize to variables that we observe after the intervention, but for

which we assume that they, firstly, affected the decision to connect and that they, secondly, are not affected by the electrification intervention.

In our data the following variables meet the requirements of affecting both the decision to connect and the impact indicators as well as being non-responsive to the treatment: the household head's education in years of schooling and a dummy variable that indicates whether the head is male or female. Furthermore, the number of buildings the household inhabits and the number of rooms as well as a dummy variable on whether the floors are cemented are included in the probit model. All these covariates are intended to capture the pre-electrification income – in particular the housing variables are important as relatively inelastic wealth indicators. In addition, years of education also represent self-selection processes driven by information asymmetries. The number of buildings and rooms pick up the lighting demand also at the time of the connection.

The estimated propensity scores from the probit model are used in two ways to identify comparable households. First, we stratify the subsample from the non-access villages into those that are likely to get connected, once the grid is available, and those that are likely not to get connected (Section 4.4). The *hypothetically connecting* households are then compared to the actually connected households. Second, we employ state-of-the-art propensity score matching algorithms to individually assign comparable connected and non-connected households to each other (Section 4.5).

4.3 Propensity score estimation

Table 3 depicts the results of the estimated probit model with the connection status as dependent variable and using households from the access region only. As can be seen, most variables have

statistically significant coefficients at the 1 % level and the fit reflected by the Pseudo R2 is fairly high at 0.36.

The coefficients from this model are used to predict the probability to connect, also referred to as *propensity score*. These propensity scores are used to stratify the non-access households into those that are likely to connect and those that are not likely to connect once electricity is available. We assume that those households that exhibit a propensity score larger than 0.5 belong to the former group. We refer to them as the *hypothetically connecting*. The quality of this prediction can be examined by means of the estimated propensity scores of effectively connected and non-connected households in the access region. In fact, we correctly predict the decision to connect for 78 % of households who decided to connect and for 75 % of households who decided not to connect.

Table 3: Probit regression of connection status on decision-to-connect determinants

Covariate	Coefficient	Standard error	p-value
Years of education of HH head	0.058***	0.224	0.01
Female HH head	-0.151	0.245	0.54
Floors are cemented	1.322***	0.195	0.00
Number of buildings	0.416***	0.108	0.00
Number of rooms	0.219***	0.074	0.00
Pseudo R2	0.363		
Likelihood ratio test statistic (X^2)	130.93***		

Note: ***,** and * indicate significance levels of 1%, 5% and 10%, respectively.

4.4 Stratified matching

We use this stratification to obtain a comparison group for the connected households that is more appropriate than the non-connected households from the access region. Indeed, comparing

connected households to the hypothetically connecting households from the non-access region we see, as shown in Table 4 that the difference in means decreases substantially for all outcome variables and becomes insignificant for *kids studying at home* and *energy expenditures* per capita. Lighting hours remain – in line with intuition – strongly significant. Also the difference on *income* is still significant at the 5 % level.

Table 4: Comparing connected and hypothetically connecting households

Outcome Indicator	Access region		Non-access region	t-statistic for test on difference in means...	
	Connected HH	Not connected HH (access region)	Hypothetically connecting HH (non-access region)	connected vs. non-connected	connected vs. hypothetically connected
Lighting hours per day	20.4	2.9	6.89	13.4***	7.5***
Kids studying at home (in hours)	1.12	0.56	1.08	4.1***	0.2
Energy expenditures per adult equivalent (in FRw)	2192	1169	1462	3.1***	1.6
Total HH income per work age adult (in 1000 FRw)	564.2	191.5	392.5	5.6***	2.0**

Note: The six households (HH) in the non-access regions who own a generator do all exhibit a propensity score larger than 0.5 and belong to the hypothetically connecting group. ***,** and * indicate significance levels of 1%, 5% and 10%, respectively.

We found in Section 3 – in line with methodological expectations – that the comparison of connected and non-connected households in the access region is not appropriate due to strong differences in socio-economic characteristics. Likewise, the question now is to what extent the comparability of the groups has improved by identifying the hypothetically connected households.¹² As proposed by ROSENBAUM AND RUBIN (1985) we scrutinize this by looking at the differences in means on the covariates between the connected and the hypothetically connecting

¹² IACUS, KIND AND PORRO (2008) criticize that many applications of matching procedures do not check for whether the comparability is actually increased.

households. As can be seen in Table 5, the difference between the groups to be compared becomes substantially smaller if the non-connected households from the access region are replaced by the hypothetically connecting ones from the non-access region. In the case of the cemented floors covariate the sign of the difference even turns around and is now significantly negative.

Table 5: Balancing between connected and hypothetically connected households

Covariate	Connected vs. non connected HH in access region	t-statistic on difference in means	Connected vs. hypothetically connecting HH	t-statistic on difference in means
Years of education of HH head	3.5	6.5***	0.7	1.1
Female HH head	-0.12	2.4**	-0.05	1.0
Floors are cemented	0.55	10.8***	-0.18	3.6***
Number of buildings	0.74	6.6***	0.10	0.7
Number of rooms	0.88	5.2***	-0.04	0.2

Note: ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

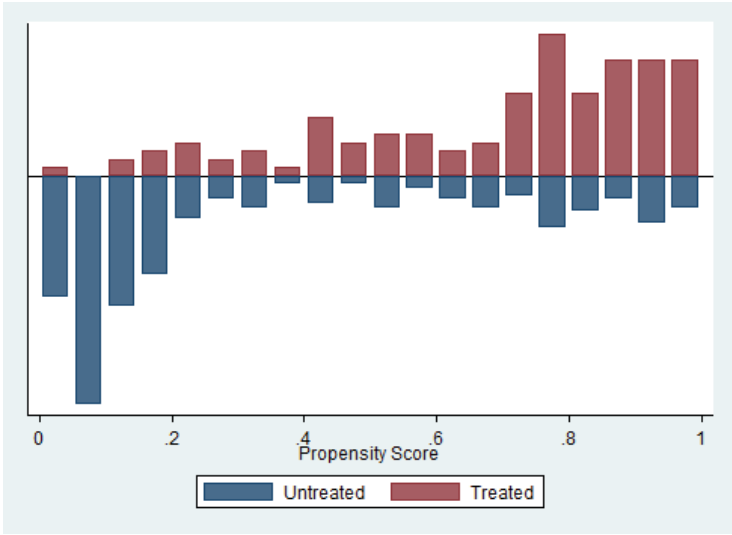
In addition, a further matching quality indicator is applied as proposed by SIANESI (2004): The probit model regressing the connection status on covariates is estimated first with all households and then with the matched ones only. By comparing the pseudo-R2 before and after, we can see if any systematic difference in the distribution of covariates between connected and non-connected households remains. The pseudo-R2 will fall after matching if a balance improvement is expected.¹³ Running the probit model again using this time the connected and hypothetically connecting households only gives us a pseudo-R2 of 0.08 compared to 0.36 using the households from the access region only (see Table 3). While the substantial decrease is supporting the success of the matching procedure, the respective Chi Squared statistic still shows a joint significant influence of the covariates. In sum, the prediction of hypothetically connected households seems to

¹³ These matching quality tests are also used in BECERRIL AND ABDULAI (2010) and PETERS, VANCE, AND HARS DORFF (2011).

yield a more reasonable comparison group, although slight discrepancies remain as indicated by the non-balancing in one covariate and the explanatory power of the post-matching sample.

Further examination of the propensity scores in Figure 2 shows that the reason for this persisting imbalance of the two groups stems from an unequal distribution of the propensity scores in the two groups. While a common support between the groups is given across the full range of the estimated score, a number of connected *treated* households exhibits very high propensity scores while only few non-access *untreated* households do so. For the calculation of the treatment effect depicted in Table 4 all non-access households with a propensity score larger than 0.5 are drawn on – equally weighted irrespective of their individual propensity score.

Figure 2: Propensity score distribution of connected households and non-access households



Therefore, in Section 4.5 we make more detailed use of the information contained in the propensity score by individually assigning matching partners, or using weights accordingly. An additional

benefit compared to the stratification approach is that the comparability is improved by also including non-access households with propensity scores below 0.5. Although the predictive quality of our probit model is quite satisfactory, still 20 % of connected households exhibit propensity scores below this benchmark.

4.5 Nearest neighbour and kernel matching

In the following, we use the estimated propensity scores from the probit model in Table 3 to match connected households individually to the hypothetically connecting households, our control households. For this purpose, we apply state-of-the-art matching algorithms. We start out by matching the *nearest neighbour without replacement* (NN). For each connected household, the NN algorithm picks a control household that has the closest propensity score for comparison. This is done as long as the connected household is in the area of common support where the propensity scores of the control households overlap with those of the connected ones. Accordingly, connected households that exhibit propensity scores higher than the highest control propensity score or lower than the lowest control propensity score are dropped¹⁴. Hypothetically connecting households act as control households only for a single connected household (without replacement).

A potential risk of NN without replacement is that “bad” matches are used to determine the treatment effect: Apart from households outside the common support, the algorithm always selects a matching partner, even if its propensity score value differs largely from that of the respective connected household. In order to check the robustness of results with respect to this

¹⁴ In order to avoid that important outliers are dropped by the common support rule we also apply the respective algorithm without employing common support. Since the results are robust in all cases, we do not display them in the tables.

feature, we also apply a *Kernel* matching algorithm. Kernel takes each connected household and uses *all* control households as individual comparison group. It weights the influence of each control household according to the distance between its propensity score and the one of the selected connected household. Implicitly, Kernel is applied with replacement.

Table 6: Treatment effects using propensity score matching (connected vs. control households)

Matching Algorithm	Outcome Indicator	Treatment effect	t-statistic for test on treatment effect	Number of observation	
				treated	untreated
Lighting hours	Nearest Neighbour	13.8	9.22***	122	399
	Kernel	13.4	9.48***		
Kids studying at home (in hours)	Nearest Neighbour	0.31	2.20**	74	201
	Kernel	0.23	1.55		
Energy expenditures per adult equivalent (in FRw)	Nearest Neighbour	626.4	1.48	102	382
	Kernel	719.7	1.90*		
Total household income per work age adult (in 1000 FRw)	Nearest Neighbour	204.2	2.58***	122	399
	Kernel	174.8	2.55**		

Note: Only observations on support are counted. The sample for kids studying at home comprises only households that have children at primary school age (275). ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

The matching results are depicted in Table 6. *Lighting hours* are substantially higher in connected households with the difference being significant at the 1 % level for both NN and Kernel matching. The magnitude of the difference amounting to more than 13 hours becomes clear when looking at the average levels of lighting consumption among connected and control households, which are at around 25 and 3 hours, respectively (see Table 2 in Section 3). For the *kids studying at home* indicator we find a small difference: Primary school children in connected households study around 20 minutes more per day than children in control households. Its significance goes beyond the 10% boundary when Kernel matching is applied, but still remains at 12 % level. Energy expenditures are higher in connected households, also after matching. While the difference of

around 700 FCFA is at best marginally significant given levels of 14 % (NN) and 6 % (Kernel), respectively, the coefficient is of notable magnitude taking into account the average weekly per adult equivalent energy expenditure in the region of 1250 FCFA. Apparently, take-up of new services and more intensive lighting usage overcompensates the efficiency increase after the switch from traditional sources to electricity. The *income* indicator also shows a considerable difference between the matched groups: While the average income is 276 000 FCFA, the matched difference is at 170 000-200 000 FCFA and statistically significant using both matching algorithms.

A caveat at this point might be that, due to the simultaneity described in Section 4.2, the selection into treatment process is particularly strong when investigating income as an indicator, so that it might not be captured sufficiently by the covariates. This concern is underpinned by the fact that connected households do not use many electric appliances or machines that can be used for income generating productive purposes. On the other hand, it might as well be the case that households perform better on labour markets thanks to improved lighting and information services.¹⁵ Nevertheless, it seems recommendable to interpret the results for the income indicator with caution.

Again in line with ROSENBAUM AND RUBIN (1985), we investigate the quality of our propensity score matching by looking at the differences in means of the covariates for connected and control households. Concretely, we look at the respective *t*-statistics for the unmatched sample and the matched one using the NN algorithm. Although, in principle the matching procedure and, hence,

¹⁵ BANERJEE AND MULLAINATHAN (2008), for example, propose a theoretical model in which individuals allocate scarce attention between problems at home and problems at work, leading to a poverty trap. By virtue of access to quality infrastructure like reliable electricity and the consequent opportunity to use distraction-saving goods and services at home labour productivity may be enhanced and this trap may be overcome.

the matched subsamples are the same for all outcome indicators, the numbers of observations differ because of missing values or not applicable items. In Table 7, we therefore show the difference in means differentiated by the respective outcome variable. With the exception of *years of education* the difference is non-significant in the matched sample. While Table 7 does only show the balancing for NN matching, the balancing of the matched samples using the Kernel algorithm is even slightly better with all significant differences becoming insignificant.

Table 7: Balancing on covariates: t-statistics for test on difference in means between treatment and comparison group

	Lighting hours and income		Energy expenditures		Kids studying at home	
Covariate	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched
Years of education of HH head	8.56***	1.66*	7.28***	0.63	6.89***	2.18**
Female HH head	1.48	0.18	-1.00	0.37	-2.41**	-1.13
Floors are cemented	10.88***	-0.01	9.72***	0.01	8.89***	0.81
Number of buildings	7.19***	1.36	6.29***	0.65	5.48***	1.11
Number of rooms	5.52***	-1.05	5.28***	-1.27	5.18***	0.58

Note: Although the matching process is the same in principle for all outcome variables, the Pseudo R²s differ because of different numbers of observations due to missing values or not applicable items. Only *Lighting hours* and *income* are based on the same number of observations. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

In addition, in Table 8 we compare the Pseudo R² as described in Section 4.2 (see also SIANESI 2004). For all outcome variables and both NN and Kernel matching the Pseudo R² decreases considerably. The chi squared statistic testing the joint significance of all covariates is significant at the 1 % level before matching and becomes insignificant after matching. This indicates that there is a systematic difference between the groups of connected and non-connected households that disappears if the matched non-connected households are taken to form the new comparison group.

For a further robustness check we modify the specification of the probit model that is used to estimate the propensity score. We included variables as covariates that one might expect to have some influence on the connection decision and the outcome variables such as household size or the age of the household head.

Table 8: PSM quality indicators before and after matching

Outcome indicator	Matching Algorithm	Pseudo R2	Pseudo R2 after	Chi Squared test statistic	
		before matching	matching	before matching	after matching
Lighting hours and income	Nearest Neighbour	0.24	0.02	138.4***	6.8
	Kernel		0.01		3.2
Kids studying at home	Nearest Neighbour	0.30	0.04	97.9***	8.0
	Kernel		0.01		2.3
Energy expenditures	Nearest Neighbour	0.22	0.01	111.5***	3.2
	Kernel		0.01		1.7

Note: Although the matching process is the same in principle for all outcome variables, the Pseudo R2s differ because of different numbers of observations due to missing values. Lighting hours and income are based on the same number of observations. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

While we could not confirm this supposition in the data and, hence, did not include them in our probit specification depicted above, the treatment effects do not change substantially if one bases the PSM on a probit model that includes these variables. Both direction and significance of the result remain constant. The balancing, in contrast, is worse than in the procedure that we selected for presentation in this paper.

5. Conclusion

This paper examines the effect of electrification status on lighting usage, education and income using cross-sectional data from rural Rwanda. The household data was collected in villages with access to the grid on the one hand and in villages without access to grid electricity on the other hand. These villages were selected according to specific comparability criteria. The inspection of

socio-economic living conditions reveals that, nevertheless, differences between the two types of villages exist that are, however, mostly driven by the connected households. We therefore apply a propensity score method in order to identify households among the non-access regions that are likely to connect to an electricity grid – if it were available. Referring to these households as the hypothetically connecting households and comparing them to the already connected households we approximate a more proper counterfactual situation and respond to distorting effects of selection into treatment processes that can be expected to be rather strong in electrification interventions.

The impact indicators we investigate are hours of lighting usage, the time primary school children dedicate to studying at home, energy expenditures and income per working-age adult. We find strong and significant effects on lighting hours, thereby confirming that the service is actually used by the households. We also obtain small positive effects on the *kids studying at home* indicator, which are significant at conventional levels in one of two matching variants we apply. While theoretically one could expect connected households to pay less for energy sources we find a substantially higher energy bill among the connected households. This indicates that increased energy consumption due to new appliances like television outweighs the efficiency increasing effect for lighting devices. Connected households also exhibit a significantly higher income than their matched non-connected counterparts. This result has to be valued against the backdrop of a potentially remaining bias for the income indicator, where we deem the selection into treatment process to be particularly strong.

Overall, we find a rather robust indication of positive effects of electrification on social and economic indicators. In particular, the importance of the substantial take up of electric lighting

must not be underestimated. Although the linkage to MDG relevant indicators is certainly not always visible in the short run, electric lighting can be expected to change life in newly electrified communities profoundly and sustainably. As qualitative communication with many villagers in different African countries has shown, it is first and foremost lighting that forms the major appeal of electricity for rural people. Referring to the historical development in Europe, FOUQUET AND PEARSON (2006) might not exaggerate in stating that the improvements in access to high quality lighting “may have changed the way we think about and sense the world – less dependent on the sun and moon, less afraid of the dark and distancing ourselves from the communal fire”. They furthermore claim that “our ability to live and work in a well-illuminated environment has radically transformed the economy and society of industrialized countries”. These impacts that go beyond the narrow focus on the MDG have to be taken into account in the evaluation of electrification policies and, hence, in further research. This might include studies that examine the long-term effects of lighting access as well as the willingness-to-pay of rural people for electricity, thereby gauging the *true* value that non-access people assign to modern energy.

Methodologically, the analysis in this paper underlines the idea of doing cross-sectional evaluations of electricity take-up and impacts – also before the project starts. The prediction of connection probabilities used in Section 4.3 seems to be quite successful. While not in the focus of this paper, this method could as well be used to approximate not only impacts but also electricity consumption in areas that do not dispose of electricity access yet. This information is of high relevance for the dimensioning of the power plants and grids to be established. The grid’s and plant’s dimension, in turn, is a major cost determinant in mini-grid electrification projects.

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