Is Electri cation Welfare Improving?: Non-Experimental Evidence from Rural Bhutan.

Kumar, Santosh and Rauniyar, Ganesh

Harvard University, Asian Development Bank

20 February 2011

Is Electrification Welfare Improving?: Non-Experimental Evidence from Rural Bhutan.

Ganesh Rauniyar* Santosh Kumar†

Draft

Abstract

This paper investigates the income and educational impacts of a large village-based electrification program in rural Bhutan. We designed and administered a household and village-level socio-economic survey in the electrified and non-electrified villages and collected data on wide range of developmental outcomes. Using Propensity Score Matching (PSM) and propensity-based weighted regression, we find that access to electricity improved economic and educational outcomes. While access to electricity increased non-farm income by 60-70%, and it had no significant effect on farm-income. Since non-farm income consists of a small percentage of total household income, the impact should be considered modest and not large. We also find that children in electrified households have 0.75 additional years of schooling, an increase of about 24%. Additionally, amount of evening study time at home is 10 minutes more for the children in the treated households compared to untreated households. We employed different matching algorithms and our results are consistent and robust to all matching estimator. Our study contributes to the few studies on infrastructure literature which has often been focused on transport, telecom, and water projects. Given the limited use of electricity for income-generating activities in Bhutan, investments in other complementary infrastructure, such as, markets, roads, information technology, credit may help the households to realize the full benefits of electrification.

JEL classification: N75, O18, O20.
Keywords: Rural Electrification, Development Effectiveness, Asian Development Bank, Impact Evaluation, South-east Asia Bhutan.

*Senior Evaluation Specialist, Independent Evaluation Department, Asian Development Bank, Philippines, Manila. (email: grauniyar@adb.org)

†Research Fellow, Harvard Center for Population and Development Studies,9 Bow st, Cambridge, MA, 02138 (e-mail: kumar@hsph.harvard.edu). We thank Kavita Sivaramakrishnan for helpful discussion. Please do not cite without author's prior permission. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors and do not necessarily represent views of the Asian Development Bank.

1 Introduction

The United Nations Millennium Development Goals (MDGs) were adopted in 2000 with the commitment to end poverty as well as improve health and education in the world's poorest countries by 2015. The MDGs emphasize poverty reduction in terms of income and highlight the importance of improved health, universal primary education, women's empowerment and gender equality, and environmental sustainability. However, many believe that none of the MDGs can be met without major improvement in the quality and quantity of energy services in developing countries. This belief is based on the premise that providing people with electricity is often a precondition for solving the eight other problems outlined in MDGs. And this led to a growing movement in 2010 to add a ninth goal in the MDGs- ending energy poverty.

Some 1.6 billion people lack access to electricity (UN, 2010) and erasing energy poverty is crucial for meaningful rural development and poverty reduction. It is universally accepted that electrification impacts income directly and education, health, environment and gender issues indirectly, but lack of data and tricky identification have constrained our understanding of the extent of impacts of electrification.[1] The absence of systematic empirical evidence on returns to infrastructure, such as electrification is striking, and estimating its impacts can be of tremendous policy relevance. This paper aims to provide such evidence.

Taking advantage of tailor-made household and village survey specifically designed for this study, we examine the impact of large village-based rural electrification program in Bhutan.[2] A major challenge in the program evaluation is to tease out the causal impact from mere correlation. A simple comparison of outcomes in households with and without electricity is unlikely to provide a causal estimate of the impact of electricity, since households with and without electricity are likely to differ along many other dimensions, such as education level, family size, amount of land etc. To address this issue, we employ a non-experimental method, commonly used in program evaluation, Propensity Score Matching (PSM) to estimate the causal impact of access to electricity on income and education in rural parts of Bhutan.[3]

In the absence of baseline data, we use rich set of household and village level variables from endline survey to generate the propensity score, and then match the electrified households with the non-electrified households.[4] We estimate the program impacts by comparing average outcomes between electrified households (hereinafter, referred as Treatment) and non-electrified households (hereinafter, referred as Control) in the matched sample. For comparison and robustness, we also use propensity-based weighted regression, in which weight is defined as the inverse of the propensity score $1\backslash\ \hat{\lambda}$ for treated households and the inverse of one minus the propensity score $1\backslash$ 1-$\hat{\lambda}$ for untreated households (See Dinardo, Fortin, and Lemieux, 1996; Hirano, Imbens,and Ridder, 2003).

We focus on both income and education as outcome variables to better understand the precise mechanism through which electricity affects rural development. The main findings of our paper is that access to electricity has positive and substantial impacts on household's income and children's education. However, results are significant only for non-farm income. Depending on matching algorithms, non-farm income in electrified households increased by 61% to 77%. Our second set of results relate to education of children. Children in treated households have 0.5 to 0.7 additional years of schooling, an increase of 24% and evening study time at home increased by 14% due to electrification. Our results are robust to different matching estimator, and when we use propensity-based weighted regression, results do not change qualitatively.

The remaining sections of the paper are organized as follows. Section 2 provides the overview of rural electrification in Bhutan and related literature. Section 3 presents empirical framework. Section 4 describes the data and sample. Section 5 presents our findings. Finally, Section 6 concludes.

2 Background and Previous Literature

2.1 Background

2.1.1 Rural Electrification in Bhutan

Bhutan is situated in the Himalayas bordered by India in the south and China in the north. With an area of 38,394 square kilometers, Bhutan is entirely a mountainous country rising from the southern foothills of 160 meter above sea level extending into the northern mountain peaks of over 7,500 meter high. Over seventy percent of the country is covered by natural forests. As per the first census conducted in 2005, the total population of Bhutan is 634,982 persons, out of which 52.5% are males and 47.5% are females. Subsistence agriculture, hydroelectricity and tourism are the main components of the Bhutanese economy. Agriculture is the occupation of 63% of the population mostly in the form of subsistence farming and animal husbandry. At the end of ninth five year in 2007, about 60 percent of Bhutanese population were connected to grid electricity.

Due to rugged terrain and the scattered nature of human settlements, extending basic services, including electricity, to its rural population has been a major challenge for the Royal Government of Bhutan (RGOB). Bhutan has substantial clean and renewable hydropower generation capacity, though electrification throughout the country has been limited. The concept of "Gross National Happiness" (GNP) was first coined in Bhutan and access to electricity has been identified as an important indicator of GNH (Planning Commission, 2000).

2.1.2 Assistance from Asian Development Bank

Power sector development has been a major element of the ADB country partnership strategy for Bhutan. ADB has supported the Royal Government of Bhutan in extending rural electrification to remote areas and in implementing a series of power sector reforms. ADB has been instrumental in improving the efficiency of hydropower generation. Bhutan's rural electrification program dates back to 6th Five Year Plan (FYP) (1986-1992) when the first unit of Chhukha hydropower plant was commissioned in 1986, however, lack of financial and human resources, coupled with a mountainous terrain halted the pace of the electrification program. Obtaining its first power loan from the Asian Development Bank (ADB) in 1995 was therefore a shot in the arm for the country's ambitious and much needed rural electrification program. Subsequent financial resources made available by ADB and other multilateral financing institutions paved the way for fulfilling the vision of electrifying the whole country, as envisioned in the 6th FYP.

ADB supported Bhutan's rural electrification program through three consecutive loans since 1995. The first loan of $7.5 million, disbursed in September 1995, provided electricity access to 2,982 new households, mainly in rural areas.

The second loan of $10.0 million was provided in May of 2000 to further electrify 6,038 consumers in 16 districts, including 23 hospitals, 24 schools, and other public facilities for local communities. The project was completed in January 2006, and provided grid connection to 8,090 new rural consumers, 32% more than envisaged, at a cost per connection of $1,454.

The third loan of $9.4 million was disbursed in November 2003 and the project was envisaged to electrify about 8,000 rural households and a population of about 50,000 in eight districts. At the end of the project in December 2006, 9,206 new rural consumers (8,857 households and 349 institutions) were connected at a cost per connection of $1,447. Due to financial and technical support from ADB and other multilateral donors, the electrification rate increased from a low 20% in 1995 to 60% in 2007. As per the Rural Electrification Master Plan, the Royal Government of Bhutan has set the target to achieve 100% electrification by 2013.

2.2 Related Literature

We are aware of two recent studies on the causal estimate of electrification on income and education: Barnes, Khandekar, and Samad (2009a) Barnes, Khandekar, Minh, and Samad (2009b), both are Policy Research Working Paper of the World Bank.[5] Barnes (2009a, 2009b) examined the impact of rural electrification on income and educational outcomes in Bangladesh and Vietnam, respectively. Both studies are an improvement over the previous studies on the impact evaluation of access to electricity. Rather than showing mere association between electricity and outcomes, these two studies provide causal estimates of electrification on income and education by employing a combination of econometric techniques, such as, Propensity Score Matching (PSM), Instrumental Variable (IV), and Difference-in-Differences (DID).

Using a cross-sectional survey conducted in 2005 of some 20,000 households in rural Bangladesh, Barnes et.al. (2009a) examine the impact of electrification on household's welfare. By employing different variants of PSM, they find that access to electricity increases household income and education of children. Electrified households have 15.4% more per capita expenditure and 30% more total income compared to non-electrified households. They find qualitatively similar results in the IV estimation, where distance of house from an electricity pole is used as an instrument for access to electricity.

Barnes et. al. (2009b) evaluates the impacts of electrification in Vietnam using a difference-in-differences design. They estimate three different models - simple difference-in differences (DID), DID with fixed-effect, and finally, DID combined with fixed-effect and propensity score matching. In the simple DID model, they find a positive and significant impact on total income, but surprisingly electricity had no significant impact on per capita expenditure. A further disaggregated analysis of total income demonstrated an insignificantly negative impact on farm income and positive impact on non-farm income. Electrified households had 36.2% higher total income and 70% higher non-farm income than the un-electrified households. The impact on boys' completed years of schooling varied from 0.52 to 0.67 years (the estimates in Bangladesh ranged from 0.09 to 0.28 years). Girls' completed years of schooling in electrified households increased by 0.14 to 0.39 years, but these impacts were insignificant at any level of significance. In Bangladesh, the corresponding estimate ranged from 0.12 to 0.36 years. It should be noted that impact on girls' completed years of schooling is similar in Bangladesh and Vietnam, whereas estimates differ substantially for boys in the case of boys.

Furthermore, the Vietnam study also finds statistically significant differences in school enrollment between electrified and non-electrified households. School enrollment for children in electrified households was approximately 11% and 10% higher for boys and girls, respectively than children in non-electrified households. Barnes (2009a) show that electrification also improved children's study time at home and the estimates ranged from 4.9 minutes to 18.2 minutes.

There are other studies on the impacts of electricity on socio-economic outcomes. However, most of these studies so far have relied on cross-sectional surveys comparing households with and without electricity, without adjusting for observed and unobserved selection biases. For example, the Independent Evaluation Group (IEG) of the World Bank analyzed Living Standard Measurement Survey (LSMS) from Peru, Ghana, Philippines, Lao PDR to study the impact of rural electrification on microenterprises. The findings of the study were as follows: (1) access to electricity increased hours household members put into the business; (2) access to electricity increased use of equipment and tools, thereby increased productivity; (3) access to electricity coupled with improved community infrastructure increased profits. Electricity also play an important role in improving agricultural output and income (Ranganathan and Ramanayya 1998; Barnes and Binswanger 1986). An USAID evaluation of rural electrification in Bangladesh (Barkat et. al., 2002) find that the average annual income of households with electricity is 64.5% higher than that in the households of non-electrified villages, and 126.1% higher than that in the households without access to electricity in electrified villages. The overall average annual (last year's) expenditure in the electrified households was more than the corresponding figure for the non-electrified households in electrified villages and for households in the non-electrified villages. The study also found a positive impact on irrigation, agricultural production, increased business turnover, and greater commercial activities.

With regard to educational outcomes, IEG of the World Bank analyzed the Demographic and Health Survey (DHS) from 9 countries and estimated a Proportional Cox hazard model (where the hazard is dropping out of school) to assess the impact of RE on children's dropout rate. The study reports higher propensity of child in electrified households to stay in school. However, the study could not confirm that this effect is mediated through an increase in reading/studying hours due to illumination after dawn. Similarly, ESMAP study in Philippines finds that children in electrified households have almost 2 years higher schooling than children in non-electrified households (8.5 versus 6.7 years).

Our study is related to two aforementioned studies by Barnes et. al. (2009a, 2009b). Similar to their work, we use propensity score matching to adjust for selection bias based on observed variables. Furthermore, this study makes several novel contributions. It adds to the few studies on infrastructure literature which has often focused on the impact of telecommunication, transport, and water projects. Additionally, the study uses data specifically designed and collected for this study, adding credibility to the estimates. Finally, it contributes to growing literature on impact evaluation, that informs evidence-based policy formulation.

3 Empirical Framework

The objective of this study is to estimate causal impact of access to electricity on household welfare, indicated by income and educational outcomes. Estimating the impact of infrastructure projects is a major methodological challenge because of absence of counterfactual state (Heckman and Robb 1985). For example, in this study, we can observe households either with access to electricity or without, but cannot observe outcomes for the same households in both states. The most convincing approach to solve this missing data problem is to conduct a randomized experiment where the counterfactual is created from a random subset of the eligible population.

Since it is nearly impossible to randomize large-scale infrastructure projects, we rely on observational data, and use non-experimental method, propensity score matching to estimate the impact of electrification on income of household and education of children. In seminal work, Rosenbaum and Rubin (1983) proposed propensity score matching as a method to reduce the bias in the estimation of treatment effects with observational data sets. In recent years, matching methods have become increasingly popular and widely used in the evaluation of economic policy interventions (Becker and Ichino, 2002; Ravallion, 2008).

The estimation of the treatment effect in observational studies may be biased due to confounding factors, because subjects are assigned to the treatment and control groups non-randomly. Propensity score matching is an alternative to "correct" this bias by creating treated and control groups that have similar covariate, and are not confounded by differences in observed covariate distributions. The idea is to generate groups of treated and control that have similar characteristics so that comparisons can be made within these matched groups. In the event of a large number of observed characteristics, direct matching becomes infeasible and propensity score *p(X)* (a single-index variable) can be used (Rosenbaum and Rubin, 1983). Propensity score *p(X)* is the estimated probability of receiving treatment given background covariates. We matched treated households with control households based on propensity score and the difference in the mean outcome of treated and control groups is attributed to the program, under the assumption that selection into program participation is based only on observables and not on unobservables.[6]

3.1 Average Treatment Effect on the Treated (ATT)

Let Y_{1i} and Y_{0i} are the outcome variables for treated and control households, respectively, and $D \in \{0, 1\}$ is the indicator of treatment status. The propensity score *p(X)* is defined as the conditional probability of receiving treatment given observed characteristics:

$$p(X) \equiv Pr(D = 1 \mid X) = E(D \mid X) \tag{1}$$

where X is the multidimensional vector of observed characteristics.

Given the propensity score *p(X)*, the Average effect of Treatment on the Treated (ATT) can be estimated as follows:

$$\begin{aligned} \widehat{ATT} &\equiv E\{Y_{1i} - Y_{0i} \mid D_i = 1\} \\ &= E[E\{Y_{1i} - Y_{0i} \mid D_i = 1, p(X_i)\}] \\ &= E[E\{Y_{1i} \mid D_i = 1, p(X_i)\} - E\{Y_{0i} \mid D_i = 0, p(X_i)\} \mid D_i = 1] \end{aligned} \tag{2}$$

Equation (2) gives the average program impact under the conditional independence assumption (CIA)[7] and overlap assumption.[8]

3.2 Matching Algorithms

In this paper, We employ four most widely used matching methods: Nearest-neighbor (NN) matching with replacement, Caliper matching, Local-linear matching, and Kernel matching. We use different matching methods to probe the robustness of the results.

3.2.1 Nearest Neighbor and Caliper Matching

With nearest-neighbor matching, the individual from comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score. We adopt nearest neighbor matching algorithm with replacement which has the merit of decreasing the bias.[9] However NN matching faces the risk of bad quality if the closest neighbor is far away. We avoid this by imposing a tolerance level on the maximum propensity score distance (caliper), this is known as caliper matching. Applying this option, means that an individual from the comparison group is chosen as a matching partner for a treated individual that lies within the caliper (propensity range). Formally, the NN matching estimator with replacement within caliper is,

$$\widehat{ATT} = \frac{1}{N1} \sum_{i=I} \{Y_i - Y_j\} \tag{3}$$

For a pre-specified caliper $\delta > 0$, j is chosen such that,
$\delta >\mid p(X_i) - p(X_j) \mid = min_{k \in I}\{\mid p(X_i) - p(X_j) \mid\}$
If none of the non-treated units is within δ from treated unit i, i is left unmatched. We use nearest five neighbors, which takes the average outcome measures of the closest five matched control units as the counter-factual for each participant.

3.2.2 Kernel and Local-linear Matching

Kernel matching method is more efficient since it uses all untreated units, thereby reducing the variance of the matching estimates. This method match a treated unit with the weighted average score of all untreated units within a certain bandwidth. The weight is inversely proportionate to the distance between treated and matched untreated observation, farther the control observation from treated observation lower the weight. Formally, Kernel matching can be expressed as:

$$\frac{1}{n_1} \sum_{i \in I_1} \left[Y_{1i} - \frac{\sum_{j \in I_0} Y_{0j} G\left(\frac{P_j - P_i}{a_n}\right)}{\sum_{k \in I_0} G\left(\frac{P_k - P_j}{a_n}\right)} \right] \tag{4}$$

where P=Pr(D=1$\mid X$), I_1 is treated, I_0 is control, n_1 is the number of persons who are in the set $I_1 \cap S_p$ where S_p is the region of common support, G the kernel function, and a_n kernel bandwidth. Local-linear matching is similar to kernel matching but includes a linear term of the balancing score. We use bootstrap method to estimate the standard errors in all the different matching algorithms.

3.3 Propensity-based Reweighting

Another method widely used in program evaluation literature is estimation of a multivariate regression, using propensity score as sampling weights. Several studies suggest that weighting the data by propensity score balances the distribution of covariates and results in fully efficient estimates (Rosenbaum, 1987; Hirano and Imbens, 2001; Hirano, Imbens, and Ridder, 2003; McCaffrey et al., 2004). This approach uses propensity score ($\hat{\lambda}$) to weight treatment and control groups in order to make the covariate distribution similar across both groups. The weight is defined as the inverse of the propensity score $1\backslash\ \hat{\lambda}$ for treated households and the inverse of one minus the propensity score $1\backslash$ 1-$\hat{\lambda}$ for untreated households.[10] For comparison and robustness, we implement this approach by estimating the following multivariate regression with propensity score as weights:

$$Y_{ijs} = \beta_0 + \beta_1 PROGRAM_{js} + \delta X_{js} + \gamma_s + \epsilon_{ijs} \tag{5}$$

where $PROGRAM_{js}$ is the access to electricity and the equation is estimated using the weight $\hat{\lambda}$. [11]

4 Data and Sample

The Independent Evaluation Department (IED) of Asian Development bank (ADB), initiated a rigorous impact evaluation of rural electrification programs in Bhutan. The study covered two projects: (i) Sustainable Rural Electrification Project (Loan 1712-BHU [SF], henceforth RE II) and Rural Electrification and Network Expansion (Loan 2009-BHU, henceforth RE III). As mentioned before, these projects were implemented between 2000 and 2006. We collected primary data specifically designed for this impact evaluation study. The following subsection discusses the sample design and data collection methods.

4.1 Sample design

A mix of purposive and probability sampling approach was undertaken to design the sampling frame. Villages/households that were electrified under RE II and RE III constituted the treatment sample and villages that are going to be electrified under RE IV through assistance from JICA (Japan International Cooperation Agency) constituted the control sample. RE IV and JICA projects were slated to start in April, 2010, two months after our data collection was complete.

Out of 20 dzonkhags, ADB assistance to RE has been in 15 dzonkhags, of which 10 were selected purposively for this study to achieve a geographically disparate and diverse study sample.[12] The country is divided into four regions namely- Western Bhutan, Central Bhutan, Eastern Bhutan, and Southern Bhutan. Three dzonkhags (Punakha, Wangdue Phodrang, and Chhukha) were selected from West, three dzonkhags (Dagana, Trongsa, and Bumthang) were selected from Central, dzonkhags (Trashigang and Lhuentse) were selected from East, and two dzonkhags (Samtse and Sarpang) were selected from South parts of Bhutan for the survey. The criteria for selecting these dzonkhags were their precise location on the map of the country to ensure that all four regions (west, central, east, and south) are effectively represented. In the next step, to ensure the similarities between electrified and un-electrified villages, gewogs that had both electrified villages (under RE II and RE III) and non-electrified villages (villages to be electrified under RE IV and JICA) were selected. In the ten selected dzonkhags, the sampling frame consisted of 198 electrified and 277 un-electrified villages. From this sampling frame, a random sample of 2,098 households in 116 villages were administered household survey. Out of 126 villages, 71 villages were treated villages yielding a treated sample of 1,276 households, and 45 villages were control villages yielding a control sample of 822 households.

4.2 Data

The study collected both quantitative and qualitative data. Quantitative data were collected by administering a village survey and a household survey. We designed the survey instruments, and these were pre-tested and piloted in one electrified and one un-electrified village in Trongsa dzonkhag. Based on the household's responses and feedbacks during the pre-testing phase, survey instruments were modified accordingly before the actual survey. The household questionnaire collected information on a various indicators pertaining to benefits of electricity.

The household questionnaires had 22 sections. The details of various sections are as follows: (i) Household roster, (ii) Employment and occupation, (iii) Household characteristics, (iv) Land holding, irrigation, and livestock, (v) Income generating activities, (vi) Information on micro-enterprises, (vii) Sources of energy used and costs, (viii) Electric appliances ownership, (ix) Attitudes and perceptions, (x) Child education, (xi) Indoor air quality and health, (xii) Time use pattern, (xiii) Gender empowerment, (xiv) Environment, (xv) Firewood collection, (xvi) Information networks, (xvii) Credit access, (xviii) Electricity and consumer satisfaction, (xix) Safety and security, (xx) Willingness to pay for electricity, (xxi) Social and political capital, (xxii) Food security.[13]

The dependent variables in this study are income of the household, and literacy, years of schooling and study time at home (in minutes per day) for school going children who are 7-18 years old. The treatment variable is electrification status of the households and takes the value one for electrified households and zero for those that did not.

The final sample consists of 1,304 treated and 798 control households. Table 1 shows the summary statistics of the outcome variables and the explanatory variables used in the propensity score estimation. Columns 1 and 2 present means for the households with access to electricity and for those without access, respectively, and the last column, col 3, presents the means of variables for the whole sample. About 62% of the sample households are electrified and they are generally better-off than the non-electrified households in terms of income and education of children (Table 1). This is not surprising, because economic and educational opportunities may have improved with the access to electricity. The sample has an average household size of 4.37 with 71% of households being headed by male. Survey data reveals that the literacy rate of head of the household is considerably low (25%) and about 72% of them are married and have an average age of 50 years.

[Table 1]

The comparison of the first column with the second column in panel B reveals that households with access to electricity and without are not similar on a number of dimensions, indicating that the control sample may not be a valid comparison group and motivates the use of propensity score matching to make the treated and control sample comparable.

5 Results and Discussions

This section reports the findings on the impact of rural electrification on income and education outcomes. We first present unadjusted difference-in-means (naïve estimates) by comparing the outcomes in electrified and non-electrified households without applying the matching technique. Next, recognizing the limitation simple difference-in-means in establishing causality, we move on present matching based results. Finally, for robustness we also present findings from estimation of propensity-based weighted regression.[14]

5.1 Unadjusted Difference-in-means (Naïve results)

Table 2 presents the naive estimates of electrification impact on income and education outcomes. The income levels and education outcomes are higher in electrified households than the non-electrified households. The income is expressed in log form. However, the estimated difference in income is statistically insignificant while the difference in education outcomes is statistically significant. Although electrified households have higher levels of benefits compared to non-electrified households, without exploring other factors that may have led to higher welfare in electrified households, we can not assert that access to electricity have contributed to the higher levels of income and education in the electrified households. Therefore, we assess the causal impacts of electricity by applying propensity score matching method.

[Table 2]

5.2 Propensity score, Balancing test and common support

5.2.1 Propensity score estimation

As mentioned before, we estimate a logit model to estimate the propensity score.[15] We estimate two variants of this model. In model 1, we include household characteristics only, and in model 2, village-level variables are also included in addition to the household characteristics. After comparing the two models, model 2 seems a better fit, therefore, village-level variables are included in the final model that estimate the propensity score.[16]

The selection of explanatory variables was guided by conditional independence assumption (CIA) and the requirements of affecting both the decision to have access to electricity and the outcomes. These variables are household size, gender of household head, age of household head, marital status of household head, whether household head is literate, total number of literate in the household, amount of land, access to tap water, house structure, religion of the household head, whether household owns cow, bull, horse, poultry, village population and distance to dzonkhag (district) headquarter. Table 3 reports the individual coefficients of the logit model. The household size, and marital and literacy status of the head of the household do not play a significant role. The gender of the head of the household, total number of literate in the household, and structure of the house are significant and have a positive effect of being electrified. By contrast, age of the head of the household, amount of land, and distance to dzonkhag have a negative effect on the electricity access.

[Table 3]

5.2.2 Common support

Figure 1 depicts the distribution of propensity scores for electrified and non-electrified households. We observe slightly higher probability mass at higher levels of the propensity scores (greater then 0.6) for electrified households, and a higher probability mass at lower levels of the propensity score (lower than 0.6) for non-electrified households. This imply that electrified households are different from non-electrified households, and there will be a potential gain from employing propensity score matching.

[Figure 1]

The common support is he region where the propensity score has positive density for electrified and non-electrified households. Matching is impossible when there is no sufficient overlap between the electrified and non-electrified households. We implement the common support restriction by using the min-max method. Min-max method drops all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group (Caliendo and Kopeinig, 2005). Figure 2 shows that there are enough overlap between electrified and non-electrified households to make reasonable comparisons. Imposing the common support criterion results in the elimination of 20 electrified households (1.56% of the total electrified sample), and none from non-electrified households.

[figure 2]

5.2.3 Balancing test

Before estimating the program impact, it is important to assess matching quality by checking the balance of distribution of relevant variables in the treated and the control groups. We implement three balancing tests commonly employed in the matching literature, namely, t-test, standardized bias, Pseudo-R^2 (see Caliendo and Kopeinig, 2005 for detail).[17]

Results are presented in Table 4 and Table 5. As can be seen in the last column of Table 4, the respective t-statistics are virtually insignificant. Furthermore, comparing the pseudo-R^2 before and after matching in Table 5, we find that the pseudo-R^2 decreases substantially to 0.003 which is much lower than the pseud-R^2 generated prior to matching (0.067). Finally, standardized bias is lower after matching (9.53 vs 2.56), and never above a value of 5, which is well within acceptable bounds (Smith and Todd 2005b). Recapitulating, results from Table 4 and 5 indicate that the improvement in comparability of treated and control groups is persuasive and robust.

[Table 4] [Table 5]

5.3 Matching results

We start by examining how electrification have affected household income and education of children in rural parts of Bhutan. Average outcomes for the matched households using various matching estimators are reported in Table 6. Findings suggest that household with access to electricity have higher levels of income and better educational outcomes. Total household income is 20% (Col 7) to 30% (Col 3) higher in households with access to electricity but is significant only under 0.01 caliper matching. However, this may be misleading and mask the true impact of electrification. A disaggregated analysis of impact on total household income reveals that electrification had a significant impact only on non-farm income. Non-farm income is 62% (Col 7) to 77% (Col 4) higher in electrified households compared to non-electrified households and this difference is statistically significant at 1% level of significance. Impact is highest under 0.1 local linear matching (LLM) and lowest under 0.2 kernel matching.

Potentially, access to electricity can increase farm-income by increased mechanization of agricultural practices, and uptake of capital intensive technology, thus increasing agricultural productivity. This may be unrealistic in Bhutan due to mountainous terrain and smaller landholding size, coupled with the fact that most of the agriculture in Bhutan is subsistence farming. On the other hand, non-farm income may be impacted due to increase in micro-enterprise undertaking and home-based small business. Interestingly, during FGDs, many participants claimed that their income from weaving had more than doubled after they received electricity, and electrification had increased their income potential by facilitating micro-enterprise business. Many participants also reported that increased non-farm income could be associated with other micro-enterprise activities, in addition to weaving. Increased poultry production in Bhutan's southern districts was also cited as an example.

However, data analysis reflecting the impact of RE on micro-enterprise activities did not provide any consistent results, suggesting that there are no significant differences between electrified and non-electrified households.[18] At the first glance, the magnitude of electricity impact on non-farm income seems large, but we argue that in the light of the estimates found in previous studies, they are not really large. For example, Barnes et al. (2009a) found that, compared to non-electrified households, having access to electricity increases non-farm income by 56 to 90% in Bangladesh. Barnes et al. (2009b) also found that non-farm income were 70% higher in electrified households, and both studies failed to provide the mechanism or channel through which non-farm income increased in the electrified household. Furthermore, non-farm income in this study accounts for only 29% of total household income in electrified and 21% in non-electrified households; hence, the impact is modest rather than large.

Next, we examine the impact of access to electricity on education of children. Results are reported in Table 6. We consider literacy, years of schooling, and study time at home as educational outcomes. The estimates suggest that access to electricity significantly improves years of schooling and study time at home in electrified households. We find that access to electricity had an insignificant impact on literacy levels of children, except in kernel matching.

The impact on years to schooling varies from 0.54 years (Col 3) to 0.75 years (Col 7). It is highest in 0.2 kernel matching, suggesting that electrification contributes to 0.75 additional years of schooling for school going children, which is an increase of 24% at average schooling of 3.18 years for the whole sample. Table 6 also shows that childrenŠs study time at home increases by 8-10 minutes per day, implying an increase of about 14% since the average study time in the sampled households is 72 minutes per day. This result is similar to the finding reported in the Bangladesh and Vietnam study by Barnes et al. (2009a, 2009b).[19]

[Table 6]

In the preceding paragraphs, we find that access to electricity had a positive impact on educational outcomes. There are various explanations for the positive impact of electrification on schooling. Though we cannot conclusively pin down the pathways, here I describe several hypotheses consistent with the results. These hypotheses are not mutually exclusive, and may each have a part in the overall results. The most compelling explanation is the increased evening study time at home due to high-quality bright light made possible by electricity. Children's efficiency and productivity increase when they study under a bright light from electric bulbs compared to a dim flickering candles or kerosene lamp. Children from poorer families benefit most from electricity, as they had previously not been allowed to study under kerosene lamps because of prohibitive costs to the households.

The failure of teachers to take up posts in remote locations and frequent absenteeism from such postings are problems in many developing countries and Bhutan is not an exception. Electrification can be instrumental in coping with such shortage of teachers and can improve teacher quality and quantity by making rural positions more attractive to teachers (IEG, 2008). Participants in our study stated that teachers preferred to stay in electrified villages because they did not need to commute daily from their original residences. This finding is supported by increase rental accommodation in electrified villages. More importantly, villages are able to recruit and retain better-qualified, experienced teachers in electrified villages compared to non-electrified ones. Further, teachers are happy to stay in electrified villages and can also prepare their teaching lesson plans at night.[20]

5.4 Robustness check

Though the main objective of this paper is to provide a PSM estimate of electrification impact, it is of some interest to compare the PSM results with those from regression and propensity based weighted-regression. One of the drawbacks of the matching method is that during matching process, off-support observations are dropped from the analysis, making the sample unrepresentative.[21] To address this concern, an alternative strategy is to estimate an OLS model with propensity score ($\hat{\lambda}$) as weight.[22] Reweighting of data ensures that covariates are similar and balanced across the treated and control groups. The results from implementing this approach is reported in column 2 of Table 7. Col 1 reports the results from ordinary least square without weight.

Results in Table 7 are quite similar to matching results reported in Table 6. Results in column 2 show that non-farm income is 63% higher in electrified households than the non-electrified households. We do not find significant impacts on farm income and total household income. Educational outcomes are also higher in electrified households than non-electrified households. Literacy and years of schooling are higher by 2.6% and 0.54 years, respectively (Col 2). Evening study time per day for children is 10 minutes in electrified households.

To sum up, we implemented three approaches, namely, PSM, OLS, and weighted regression, to estimate the causal impact of access to electricity on income and schooling, marker of household welfare. We find that electricity contributed to the increase in non-farm income and schooling of children in rural Bhutan. Overall, results from different methodology are quite consistent in the direction and magnitude of the impacts. [Table 7]

6 Conclusion and Policy Implications

Many researchers have sought to link electricity access with broad development and poverty reduction (Cabraal, Barnes, and Agarwal, 2005; Cecelski, 2005; Karkezi, Mapako, and Teferra, 2002), but the evidence base for this link remains thin (IEG, World

Bank, 2008). What is striking in the policy debates surrounding rural electrification is the absence of systematic empirical evidence on how access to electricity affects welfare, especially of the rural poor. This study contributes to filling this research gap by exploring the causal impact of access to electricity on income and schooling in the context of large village-based electrification program in rural Bhutan.

Our matching based results indicate that access to electricity improved economic and educational outcomes. According to our findings, the impact on non-farm income due to electricity can be as high as 76%. Children in electrified households gain an additional 0.74 years of schooling and spend more time studying in the evening. Matching results are consistent and similar to results from OLS and weighted regression. Taken together, this study showed that over a short span of time, rural electrification has been instrumental in improving the quality of life of households in rural Bhutan.

The findings of this study has the following policy implication. The use of electricity for income-generating activities in Bhutan has been very limited, but the potential to increase household income is quite high. It should be noted that rural electrification is, of course, a necessary, but not sufficient, condition for expanding income opportunities. Unless substantive complementary investments in improving complementary infrastructure are made, such as, access to roads, market development, irrigation systems, skills development, and services, the demand for electricity is likely to remain below lifeline block in Bhutan in the foreseeable future for most of the households. Integrated infrastructure development can create substantial multiplier effects, thus promoting and stimulating growth in local economy.

Notes

[1]A few recent studies have addressed the causality issue, such as endogeneity of program placement and self-selection, and found significant benefits of electrification. We discuss it in section 2.2.

[2]Bhutan is situated in the Himalayas bordered by India in the south and China in the north. With an area of 38,394 square kilometers, Bhutan is entirely a mountainous country rising from the southern foothills of 160 meter above sea level extending into the northern mountain peaks of over 7,500 meter high. Over seventy percent of the country is covered by natural forests.

[3]See Ravallion (2001) for methods employed in programme evaluation.

[4]The endline survey was designed and conducted by us in 116 villages in 10 Dzonkhag in rural parts of Bhutan. We collected socio-economic data from 2,098 households- 1276 electrified and 822 non-electrified households. The survey was originally administered for conducting the rigorous impact evaluation of rural electrification projects by ADB in Bhutan.

[5]There are two more related studies that evaluate the impacts of electrification: Dinkelman (2010) and Barham, Lipscomb, Mobarak (2008), both analyze the electrification impacts on outcomes different from outcomes in our paper and are an unpublished manuscript. Dinkelman (2010) estimates the impact of electrification on employment growth in South Africa and found increased female employment due to electrification. Barham, Lipscomb, Mobarak (2008) found that availability of electricity induces migration and increases GDP per capita in Brazil.

[6]See Dehejia and Wahba (1999, 2002), Heckman et al. (1997, 1998a), Smith and Todd (2001, 2005a) for an evaluation of matching estimators.

[7]Conditional independence assumption states that conditional on X, the outcomes are independent of treatment, and can be written as Y_1, $Y_0 \perp D \mid X$.

[8]Implies that for each X there are both treated and control units, i.e. $0 < \Pr[D=1|\ X] < 1$.

[9]We used replacement method so that a single control household can be used as a match for more than one treated household.

[10]A variation of the formula with the square root is also used. We prefer the square-rooted version because it scales down the variation in weight.

[11]Propensity score ($\hat{\lambda}$) are estimated from a logistic regression. We also estimate an ordinary least square (OLS) model for income and linear probability model (LPM) for educational outcomes without reweighting the data.

[12]The Kingdom of Bhutan is divided into four dzongdey (administrative zones). Each dzongdey is further divided into dzongkhag (districts). There are twenty dzongkhag in Bhutan. Large dzongkhag are further divided into sub-districts known as dungkhag. At

the basic level, groups of villages form a constituency called gewog (blocks) and are administered by a gup, who is elected by the people.

[13] A village questionnaire was also administered to the gup or head of the village. The village questionnaire collected information on: (i) General characteristics of the village, (ii) Water and sanitary conditions in the village, (iii) Education and health infrastructure, (iv) Availability of energy, and (v) Economic activity in the village. The data collection started in January 2010 and was over by March, 2010.

[14]Difference-in-means findings are reported largely to serve as a comparison to the propensity-based matching and weighted regression estimates.

[15]Either logit or probit are generally used to estimate propensity score, however literature does not suggest which one is the preferred model. For ease of interpretation, we use logit model.

[16]Results for model 1 is not shown here and available upon request. Model fit is determined by comparing the likelihood ratio or McFadden's pseudo R-square between the two models, and they are higher for Model 2, suggesting that the appropriate model should include village-level variables as well.

[17]First, Rosenbaum and Rubin (1985) proposed to use a two-sample t-test to check if there are significant differences in covariate means for both groups. Additionally, Rosenbaum and Rubin (1985) suggested to check the standardized difference before and after matching. If the covariates are balanced, there should be a reduction in the standardized bias, this is a common approach used in many evaluation studies, e.g. by Lechner (1999), Sianesi (2004) and Caliendo, Hujer, and Thomsen (2005). Finally, Sianesi (2004) proposed to compare the pseudo-R^2 before and after matching. The pseudo-R^2 indicates how well the regressors X explain the participation probability. After matching there should be no systematic differences in the distribution of covariates between both groups and therefore, the pseudo-R^2 should be fairly low.

[18]Results available upon request.

[19]A World Bank's socio-economic impact study in the Philippines established that access to electricity was correlated with significant educational achievement (ESMAP, 2003).

[20]TV viewing may provide educational benefits through increased knowledge and awareness, though it may marginalize the evening study time for children. Other benefits may be (a) use of mass media to supplement normal classroom teaching, (b) improved performance of polytechnic schools offering vocational classes including carpentry, welding, engineering etc., and (c) by making extra teaching in early mornings and late evenings possible

[21]Though in our study only 40 observations were off-support and were dropped from the analysis.

[22]The weight is defined as the inverse of the propensity score $1\backslash\ \hat{\lambda}$ for treated households and the inverse of one minus the propensity score $1\backslash\ 1\text{-}\hat{\lambda}$ for untreated households.

References

Asian Development Bank (2008) "Report and Recommendation of the President to the Board of Directors on a Proposed Loans", Asian Development Fund Grant, Technical Assistance Grant, and Administration of Grant Green Power Development Project (Bhutan), Manila.

Barham, T., M. Lipscomb, and A. Mushfiq Mobarak (2005a) "Development Effects of Electrification: Evidence from the Geologic Placement of Hydropower Plants in Brazil".

Barkat et al. (2002) "Economic and Social Impact Evaluation Study of the Rural Electrification Program in Bangladesh", Human development Research Centre and NRECA International Ltd.Arlington, VA.

Barnes, D. F., and H. P. Binswanger (1986) "Impact of Rural Electrification and Infrastructure on Agricultural Changes, 1966-1980", Economic and Political Weekly, 21:26-34.

Becker, S. O. and A. Ichino (2002) "Estimation of Average Treatment Effects based on Propensity Scores", *Biometrika*, 70(1): 41-55.

Black, Dan A., and Jeffrey A. Smith (2004) "How Robust Is the Evidence on the Effects of College Quality-Evidence from Matching", *Journal of Econometrics*, v121 (n1-2):99- 124.

Binswanger, Hans P., Shahidur R. Khandker and Mark R. Rosenzweig (1993) "How Infrastructure and Financial Institutions affect Agricultural Output and Investment in India", *Journal of Development Economics*, 41, 337-366.

Cecelski, Elizabeth (2004) "Re-thinking Gender and Energy:Old and New Directions", ENERGIA/EASE Discussion Paper, Leusden, The Netherlands.

Chaudhury, Nazmul; Hammer, J.; Kremer, M. and Muralidharan, K.; and Rogers, H. (2006) "Missing in Action: Teacher and Health Worker Absence in Developing Countries", *Journal of Economic Perspectives*, Winter 2006, Vol. 20(1), pp. 91-116.

Diaz, Juan Jose, and Sudhanshu Handa (2006) "An Assessment of Propensity Score Matching as a Nonexperimental Impact Estimator: Evidence from Mexico's PROGRESA Program", *Journal of Human Resources*, 41(2): 319-345.

Dehejia, Rajeev H., and Sadek Wahba (2002) "Propensity Score-Matching Methods for Non-experimental Causal Studies", *Review of Economics and Statistics*, v84 (n1):151-61.

Dinkelman, Taryn (2007) "Can rural electrification jump-start employment? Evidence from KwaZulu-Natal, South Africa", Department of Economics, Princeton University, Working Paper.

ESMAP (2000) “Reducing the Cost of Grid Extension for Rural Electrification”, ESMAP Report 227/00, World Bank,Washington, DC.

ESMAP (2002) “Rural Electrification and Development in the Philippines: Measuring the Social and Economic Benefits”, Report 255/02.

Heckman, James, Hidehiko Ichimura, and Petra Todd. 1998a, “Matching as an Econometric Evaluation Estimator,” *Review of Economic Studies*, v65 (n2):261-294.

Heckman, James, Hidehiko Ichimura, Jeffrey Smith, and Petra Todd (1998b) “Characterizing Selection Bias Using Experimental Data”, NBER Working Papers: 6699.

Heckman, J., R. LaLonde, and J. Smith (1999) “The Economics and Econometrics of Active Labor Market Programs”, *Handbook of Labor Economics*, Vol.III, ed. by O. Ashenfelter, and D. Card, pp. 1865-2097, Elsevier, Amsterdam.

Independent Evaluation Group (2008) “The Welfare Impact of Rural Electrification: A Reassessment of the Costs and Benefits”, An IEG Impact Evaluation.

Khandekar et al. (2009) “Welfare Impacts of Rural Electrification: A Case Study from Bangladesh”, Policy Research Working Paper 4859, March, The World Bank.

Khandekar et al. (2009) “Welfare Impacts of Rural Electrification: Evidence from Vietnam”, Policy Research Working Paper 5057, September, The World Bank.

Jalan, J. and M. Ravallion (2003) “Does Piped Water Reduce Diarrhea for Children in Rural India”, *Journal of Econometrics*, Vol. 112(1), pp. 153-173.

Ranganathan, V. and T.V. Ramanayya (1998) “Long-Term Impact of Rural Electrification: A Study in UP and MP”, *Economic and Political Weekly*, December 12, 1998.

Ravallion, Martin (2008) “Evaluating anti-Poverty Programs”, World Bank.

Rosenbaum, Paul R. and Donald B. Rubin (1983) “The Central Role of the Propensity Score in Observational Studies for Causal Effects”, *Biometrika*, v70 (n1):41-55.

Saghir, Jamir (2005) “Energy and Poverty: Myths, Links, and Policy Issues”, Energy Working Notes, Energy and mining sector Board, The World Bank Group, No 4.

Smith, Jeffrey A., and Petra E. Todd (2005a) “Does Matching Overcome LaLonde’s Critique of Non-experimental Estimators?”, *Journal of Econometrics*, v125 (n1-2):305-53.

Songco, J. (2002) “Do Rural Infrastructure Investments Benefit the Poor?” World Bank Working Paper 2796, Washington, D.C.

Table 1: Descriptive Statistics of Outcomes and Matching Variables

Variables	Household with electricity	Household without electricity	Whole sample
	(1)	(2)	(3)
PANEL A			
Economic Outcomes			
Annual total income (Rs.)	26123.91	21044.25	24201.49
Annual farm income (Rs.)	11172.3	9454.927	10522.35
Annual non-farm income (Rs.)	7520.33	4361.48	6324.85
N	1,304	794	2,098
Education Outcomes (7-18 years old)			
Literacy	0.88	0.80	0.85
Years of schooling	3.48	2.64	3.18
Study time at home (minutes per day)	75.75	65.32	72.57
N	1,333	759	2,092
PANEL B			
Matching Variables			
Household size	4.42	4.33	4.36
Gender of head of the household (male=1)	0.69	0.73	71.21
Age of household head	49.47	49.72	49.74
Literacy level of household head (yes=1)	0.21	0.27	0.25
Total number of literates in the household	1.45	1.74	1.63
Marital status of household head	0.71	0.75	72.83
Access to tap water	0.55	0.57	56.20
Amount of land (acres)	3.76	3.24	3.39
House structure (brick=1)	0.63	0.75	0.71
Whether owns cow (yes=1)	0.78	0.76	0.76
Whether owns bull (yes=1)	0.60	0.57	0.58
Whether owns horse (yes=1)	0.19	0.16	0.17
Whether owns poultry (yes=1)	0.62	0.57	0.59
Religion of household head	0.65	0.72	0.70
Total population of the village	295.36	308.9	305.03
Distance from dzonkhag (km)	52.29	43.66	47.40
N	1,304	794	2,098

Table 2: Unadjusted Difference in Means: Naive Results

Variables	Household with electricity	Household without electricity	Difference	T-stat
	(1)	(2)	(3)	(4)
Economic Outcomes				
Annual total income (Rs.)	7.94	7.74	0.20	1.21
Annual farm income (Rs.)	5.59	5.53	0.06	0.31
Annual non-farm income (Rs.)	3.81	3.27	0.54***	3.09
Education Outcomes (7-18 years old)				
Literacy	0.88	0.80	0.08***	4.51
Years of schooling	3.48	2.64	0.848**	7.22
Study time at home (minutes per day)	75.75	65.32	10.43***	3.33

Notes: * Statistically significant at the 10 percent level; ** at the 5 percent level; and *** at the 1 percent level.

Table 3: Logit estimates of household's access to electricity

Household characteristics	Coefficient
	(1)
Household size	-0.048
	(0.093)
Square of household size	-0.007
	(0.008)
Gender of household head	0.210*
	(0.128)
Age of the household head	-0.032***
	(0.011)
Household age square	0.000***
	(0.000)
Marital status of the household head	0.170
	(0.131)
Whether household head is literate	0.060
	(0.136)
Total no of adult literates in the household	0.243***
	(0.048)
Amount of land (acres)	-0.112***
	(0.022)
Square of landholding size	0.002***
	(0.001)
Access to tap water	-0.082
	(0.099)
House structure (brick==1)	0.594***
	(0.117)
Religion	0.143
	(0.123)
Whether owns cow	-0.075
	(0.131)
Whether owns bull	0.022
	(0.113)
Whether owns horse	-0.479***
	(0.134)
Whether owns poultry	-0.141
	(0.107)
Village population	0.000*
	(0.000)
Distance to Dzonkhag (km)	-0.008***
	(0.001)
Wald	171.11
P-value	0.0000
McFadden's Pseudo-R	0.0635
N	2040

Notes: * Statistically significant at the 10 percent level; ** at the 5 percent level;

Table 4: Post-Matching Means of the variables

Household characteristics	Households with electricity	Households without electricity	T-stat
	(1)	(2)	(3)
Household size	4.45	4.31	-1.72
Household size square	24.14	22.61	-1.82
Gender of head of the household	0.73	0.73	-0.23
Age of household head	50.15	49.67	-0.71
Age square of household head	2804.6	2746.5	-0.89
Literacy level of household head (yes==1)	0.28	0.27	-0.56
Total number of literates	1.80	1.70	-1.57
Marital status of household head	0.74	0.74	0.22
Access to tap water	0.56	0.56	0.43
Amount of land (acres)	2.99	2.86	-0.92
Square of landholding	21.40	18.66	-0.56
House structure (brick==1)	0.75	0.75	-0.15
Whether owns cow (yes=1)	0.76	0.76	0.09
Whether owns bull (yes=1)	0.56	0.57	0.26
Whether owns horse (yes=1)	0.16	0.16	0.23
Whether owns poultry (yes=1)	0.58	0.57	-0.85
Religion of household head	0.69	0.72	1.44
Total population of the village	300.12	307.32	0.67
Distance to dzonkhag (km)	44.016	43.88	-0.10

Notes: * Statistically significant at the 10 percent level; ** at the 5 percent level; and *** at the 1 percent level. Matched samples are constructed using nearest neighbor with replacement and common support.

Table 5: Absolute Bias, pseudo-R^2 and LR χ^2

	Pseudo-R^2	LR χ^2	$p > \chi^2$	Standardized bias
	(1)	(2)	(3)	(4)
Unmatched	0.067	171.82	0.000	9.53
Matched	0.003	8.84	0.976	2.56

Table 6: Average Treatment Effect of household electrification: PSM Estimates

	Matching Methods						
Variables	Nearest	Caliper		Local Linear		Kernel	
	Neighbor	d=0.01	d=0.001	bw=0.1	bw=0.2	bw=0.1	bw=0.2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<u>Economic Outcomes</u>							
Total income	0.280	0.270*	0.300	0.274	0.271	0.238	0.198
	(0.217)	(0.162)	(0.240)	(0.187)	(0.194)	(0.184)	(0.169)
Farm income	0.300	0.236	0.245	0.242	0.224	0.165	0.082
	(0.30)	(0.232)	(0.252)	(0.222)	(0.198)	(0.173)	(0.190)
Non-farm income	0.687*	0.723***	0.678***	0.771***	0.760***	0.678***	0.619***
	(0.255)	(0.203)	(0.217)	(0.195)	(0.205)	(0.197)	(0.180)
<u>Educational Outcomes</u>							
Literacy	0.016	0.019	0.017	0.028	0.028	0.042**	0.057**
	(0.021)	(0.016)	(0.018)	(0.018)	(0.018)	(0.015)	(0.019)
Years of schooling	0.578***	0.603***	0.536***	0.616***	0.616***	0.686***	0.745***
	(0.124)	(0.126)	(0.140)	(0.110)	(0.139)	(0.149)	(0.127)
Study time at home	8.726	8.156*	10.125*	9.732**	9.744**	9.721***	9.366***
(minutes per day)	(5.502)	(4.822)	(5.671)	(4.182)	(4.310)	(2.997)	(3.123)

Notes: Income is expressed in log form. Bootstrapped standard errors are shown in parenthesis. Kernel uses normal density. Nearest neighbor done with replacement with five neighbors. Educational outcomes are for 7-18 years old children in the household. Economic outcomes and study time at home are at household level.
* Statistically significant at the 10 percent level; ** at the 5 percent level; and *** at the 1 percent level.

Table 7: OLS and WLS: Robustness check

	OLS	Weighted Regression
Independent	(1)	(2)
Economic outcomes		
Total income	0.131	0.245
	(0.173)	(0.175)
Farm income	0.204	0.260
	(0.189)	(0.190)
Non-farm income	0.495***	0.628***
	(0.179)	(0.181)
Educational outcomes		
Literacy	0.030*	0.026*
	(0.015)	(0.015)
Years of schooling	0.546***	0.541***
	(0.113)	(0.116)
Study time at home	10.166***	10.065***
(minutes per day)	(3.478)	(3.761)

Notes: Income is expressed in log form. Standard errors are shown in parenthesis. Linear probability model was estimated for binary outcome, literacy. Educational outcomes are for 7 to 18 years old children in the household. Economic outcomes and study time at home are at household level. * Statistically significant at the 10 percent level; ** at the 5 percent level; and *** at the 1 percent level.

Figure 1: Distribution of propensity score before matching

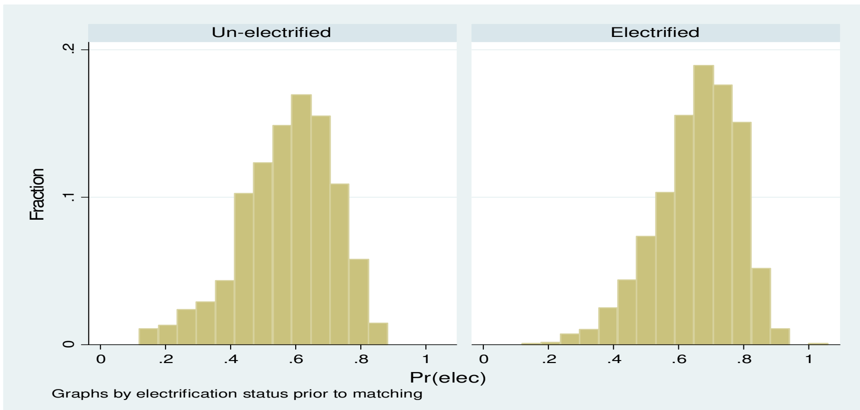

Figure 2: Validating common support