Impact of Solar Home System in Bangladesh: PSM Approach

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ABSTRACT

Principal aim of the paper is to present some assessment of the socio-economic impact of the solar Home System (SHS) in rural Bangladesh. For such purpose Propensity Scoring Method (PSM) has been adopted to data collected at household level. For matching without replacement we have considered low-to-high, high-to-low and random matching. We have also considered weighted difference in means to estimate intervention effect as well as weighted regression. Spectacular identification of impact has been obtained through PSM. Research results expose tremendous potentials for solar energy system in the context of rural Bangladesh.

Keywords: SHS, PSM, RET, non-random assignment, counterfactual, Face-to-Face interview.

1. Background

Improved access to clean and modern energy is essential to poverty reduction and reaching Millennium Development Goals (MDGs) for the developing countries. However, maintaining the traditional practice of energy consumption using fossil fuel- which is widespread among over 2.5 billion people worldwide in the developing countries-poses a grave challenge to the sustainability of the environment. That is why there has been a worldwide consensus to encourage the development of the Renewable Energy Technology (RET). One of the fast-growing RETs is the SHS, which has become a low-cost option for electricity in many countries due to the continuous cost reductions in the photovoltaic (PV) technology. And many donors and development organizations, for example the World Bank, have started promoting it as a viable source of electricity in Rural areas of developing countries where grid electricity is not feasible in the near future. Besides providing electricity in an environmentally friendly and sustainable way, SHS can also impart socio- economic benefits to the consumer households.

The SHS component of the RERED is administered by the Infrastructure Development Company Limited (IDCOL), a government owned financial intermediary. Under the SHS program, the partner organizations (POS) procure the SHS components and install them in rural households. Households pay 10-15% down payment for the systems installed and the rest is repaid under a 3-5 year micro-credit agreement with the POs. After the systems are installed the POs apply to IDCOL for refinancing and for a subsidy per system (currently US$ 28 per system). After verifications of the systems, IDCOL releases the refinancing amount and the subsidy amount to the POs using funds from the World Bank and other development partners.

The plan of the paper is as follows. In section 2 we delineate methodological issues while in section 3 we present data description. In section 4 we present research results followed by concluding remarks in section 5.

2. Methodological Issue

Although varieties of analysis tools for impact assessment are available, all of them are not equally applicable in a particular situation. Depending on the nature of the problem, some specific tools are more appropriate compared to others. For expost impact assessment like the case of ours, Instrumental variable (IV) technique, Regression Discontinuity (RD) technique, Propensity Score Matching technique and Panel data Analysis technique are good candidates. However, for our purpose, PSM has been chosen as the analysis tool and we highlight a brief exposition of the tool in this section

Random assignment is used in Experimental evaluation to assure that participation in the intervention is the only differentiating factor between units subject to the intervention and those excluded from it. Thus, the control group can be used to assess what would have happened to participants in the absence of the intervention. Considerable progress has been made, however, in understanding the effectiveness of interventions on core outcomes of interest through the application of rigorous nonexperimental evaluation methods. In addition to providing direct estimates of program effects on relevant outcomes, such methods can also address a variety of related and subsidiary questions, such as: are some interventions more effective for particular types of groups or units than others? What factors outside the control of the implementers influence outcomes, and how might the intervention be modified to account for them?

PSM uses information from a pool of units that do not participate in the intervention to identify what would have happened to participating units in the absence of the intervention. By comparing how outcomes differ for participants relative to observationally similar non participants, it is possible to estimate the effects of the intervention. Propensity-score matching, one of the most important innovations in developing workable matching methods, allows this matching problem to be reduced to a single dimension. The propensity score is defined as the probability that a unit in the combined sample of treated and untreated units receives the treatment, given a set of observed variables. If all information relevant to participation and outcomes is observable to the researcher, the propensity score (or probability of participation) will produce valid matches for estimating the impact of an intervention. Therefore, rather than attempting to match on all values of the variables, cases can be compared on the basis of propensity scores alone.

The PSM technique has been applied in a wide variety of fields in the program evaluation literature. For example, Heckman, Ichimura and Todd (1998), Lechner (1999), Dehejia and Wahba (2002), and Smith & Todd (2005) use PSM techniques to estimate the impact of labor market and training programs on income; Jalan and Ravallion (2003) evaluate antipoverty workfare programs; Faliani, Gerter and Schargrodsky (2005) study the effect of water supply on child mortality; Trujillo, Portillo and Vernon (2005) analyze the impact of health insurance on medical-care participation; Almus and Czarnitzki (2003) and Moser (2005) evaluate impact of R & D subsides & patent laws on innovations.

The greatest challenge in evaluating any intervention or program is obtaining a credible estimate of the counterfactual: What would have happened to participating units if they had not participated? One feasible solution to this problem is to estimate the counterfactual outcome based on a group and of nonparticipants. Then calculate the impact of the intervention as the difference in mean outcomes between groups and the comparison group must be statistically equivalent to the initial treated group. In other words, the groups that must be identical except for the fact that one of them received the treatment and the other not. Thus, the main concern is how to find a proper comparison group.

Suppose, the impact of a treatment for an individual i, noted ε_i is defined as the difference between the potential outcome in case of treatment (Y_{1i}) and the potential outcome in absence of treatment (Y_{oi}).

$$\varepsilon_i = Y_{1i} - Y_{0i}$$

An evaluation seeks to estimate the mean impact of the program, obtained by averaging the impact across all the individuals in the population. This parameter is known as **Average Treatment Effect or ATE:**

ATE =E(ε) = E(Y $_{1i}$ $- Y_{0i}$)

where E(.) represents the average (or expected value).

Average Treatment Effect on the Treated, or ATT, which measures the impact of the program on those individuals who participated is also of interest.

ATT = E(Y $_1 - Y_0 \mid D = 1)$

Finally, the Average Treatment Effect on the Untreated (ATU) measures the impact that the program would have had on those who did not participate:

ATU = E(Y $_1 - Y_0 \mid D = 0)$

Problem is that all of these parameters are not observable, since they depend on counterfactual outcomes. For instance, using the fact that the average of a difference is the difference of the averages, the ATT can be rewritten as:

ATT = E(Y $_1 - Y_0 \mid D = 1) - E(Y_0 \mid D = 1)$

E($Y_0 \mid D = 1)$ is the average outcome that the treated individuals would have in the absence of treatment. However, we do observe the term E($Y_0 \mid D = 0)$, the value of Yo for the untreated individuals. Thus, we can calculate:

Δ = E(Y $_1 \mid D = 1) - E(Y_0 \mid D = 0)$

What is the difference between Δ and the ATT? Adding and subtracting the term E(Y $o \mid D = 1)$:

Δ = E(Y $_{1\ i} \mid D = 1) - E(Y_0 \mid D = 1) + E(Y_0 \mid D = 1)$ - $E(Y_0 \mid D = 0)$

Δ=ATT + $E(Y_0 \mid D = 1)$ - $E(Y_0 \mid D = 0)$

Δ=ATT+SB

SB is the selection bias: the difference between the counterfactual for treated individuals and the observed outcome for the untreated individuals, If this term is equal to 0, then the ATT can be estimated by the difference between the mean observed outcomes for treated and untreated:

ATT= $E(Y \mid D=1)$-$E(Y \mid D=0)$

In many cases the selection bias term is not equal to 0. In these cases, the difference in means, will be a biased estimator of the ATT. The main goal of an evaluation is to ensure that the selection bias is equal to 0 in order to correctly estimate the parameter of interest.

We use Y_1 and Y_o to denote the potential outcomes in presence and absence of the treatment, respectively. The observed outcome Y for an individual will be Y_1 if the individual is treated and Y_o otherwise, We use the binary variable D to indicate the treatment status of the observed units. D=1 for those who participate and D=0 for those who do not participate. Then the observed outcome is:

$Y=(1-D)Y_0+DY_1$

When a given unit is treated, then D=1, and thus (1-D)=0. The observed outcome for this unit will be:

$Y=0.Y_0+1Y_1=Y_1$

which means that the observed outcome (Y) for treated units is equal to the potential outcome in case of treatment (Y_1). In this case, the potential outcome in absence of treatment, Yo, is not observed: since the unit was treated, it is impossible to know what would have happened to this unit in absence of treatment. For a treated unit Yo is the counterfactual. Similarly, when the unit is not treated, D=0 and (1-D)=1, and thusY=Yo. In this case, the counterfactual is Y_1.

Random assignment methods assure that the treatment is independent of Y_o and Y_1 and the factors influencing them. The average treatment effect for those subject to random assignment may be estimated as the simple difference in mean outcomes for those assigned to treatment and those assigned to the control group. In nonrandom assignment, treatment may be correlated with factors influencing Y_o and Y_1, participants may differ from nonparticipants in many ways. So the simple difference in outcomes between participants and nonparticipants will not necessarily identify the impact of the intervention.

Matching methods ensure that impact estimates are based on outcome differences between comparable individuals. Such approach has been adopted in the present case.

3. Data Description

There has been a study on Impact Evaluations of Solar Home System in Bangladesh in 2011. Data were collected at Household, community and market levels. At household level 12,960 respondents were included. At community level 216 union parishads (lower tier of the administrative system) and 2160 market places were brought under the survey. Data were collected using multistage stratified random sampling procedure. At first sample size of 216 unions (PSU) was determined using statistical formula with 95% confidence level and 5% precision level. It was then proportionately allotted to 7 administrative divisions. Within each division PPS was adopted to choose PSUs. However, although both quantitative and qualitative methods were adopted we have adopted PSM only to data collected through Face-to Face Interview. Such results are presented in this paper.

4. Study Results and Analysis

In this section we present our study findings in association with brief analysis.

Table 1. Sample Means

Variable	Treatment group	Control group
Years of schooling	10.36	10.08
Proportion married	0.20	0.26
Number of children	4.42	5.38
Weekly working hours	47	48
Real earnings (monthly)	3,689	3,425
Hours worked (I year) before invention	2115	2160

We notice in the above table that the two groups do not significantly differ in terms of covariates before intenvention

Table2. Household electricity access by Division

Division	HH with no electricity (%)	HH with SHS (%)	HH with grid-electricity (%)
Barisal	78.0	8.8	20.0
Chittagong	58.7	9.7	36.7
Dhaka	68.1	6.7	32.4
Khulna	60.4	8.5	34.1
Rajshahi	66.0	6.2	38.8
Sylhet	64.4	3.2	36.4
Total	63.9	7.3	32.9

Table 3. Impact of Power access on Kerosene use: Grid electricity and SHS

Expenditure per capita	Kerosene use (monthly)	Grid –electricity				SHS			
		OLS		PSM		OLS		PSM	
	(liter)	Estimate	(s.e.)	Estimate	(s.e.)	Estimate	(s.e.)	Estimate	(s.e.)
Ave effect by deciles	2.7	-1.3	0.0	-1.1	0.4	-2.6	0.1	-2.4	0.2
1	2.6	-1.0	0.0	-1.0	0.6	-2.2	0.2	-2.3	0.4
2	2.7	-1.1	0.1	-1..2	0.4	-2.0	0.3	-2.1	0.5
3	2.6	-1..2	0.1	-0.7	0.5	-2.2	0.3	-2.3	0.3
4	2.7	-1..2	0.1	-2.8	0.9	-2.4	0.2	-2.4	0.2
5	2.8	-1..3	0.1	-1..3	0.3	-2.5	0.2	-2.6	0.1
6	3.2	-1..3	0.1	-1..3	0.7	-2.4	0.2	-2..5	0.2
7	2.7	-1..4	0.1	-1..4	0.5	-2.6	0.2	-3.2	0.2
8	2.6	-1..5	0.1	-1..6	0.5	-2.5	0.2	-3.2	0.2
9	2.7	-1..5	0.1	-2.6	0.8	-3.1	0.2	-3.6	0.6
10	2.5	-1.1	0.1	-0.6	0.6	-2.6	0.2	-3.2	0.2

Propensity score is obtained using Binary probit on SHS status on covariates (age, year of schooling, income, expenditure, family size etc)

Table 4: Probability of SHS purchase among households without electricity

Log likelihood= -1746.45

SHS purchase	Z	P>|Z|	β
Log (per capita Expenditure)	4	0.00	0.13
Log (land size)	6	0.00	0.08
Non-farm income	8	0.00	0.10
Household size	4.8	0.00	0.09
Female head	1.8	0.00	0.04

It is very much clear from Table 4 above that propensity to use SHS is very sensitive to income and expenditure levels of households.

In conclusion, propensity score-matching methods are able to yield reasonably accurate estimates of the treatment impact, By selecting an appropriate subset from the comparisons group, a simple difference in means yields an estimate of the treatment effect close to the experimental benchmark. The chose among matching methods becomes important when there is minimal overlap between the tr3atment and comparison groups. When there is minimal overlap, matching with replacement emerges as a better choice. In principle, caliper matching can also improve standard errors relative to nearest-neighbor matching, although at the cost of greater bias.

Kerosene displacement

The displacement impact is statistically significant which indicates that both SHSs and grid-electricity access reduce kerosene use. The impact of SHS access is much larger on displacing kerosene than grid-electricity access. On average, the estimated kerosene displacement is about 2.6 liters/ month by OLS (compared with 1.3 from grid-electricity connection) and 2.4 liter/month by PSM (1.4 from grid connection), after controlling for household socioeconomic factors, village electrification status and location effects. The scale of kerosene displacement bears relation with household incomes: about 2.2 liters per month being displaced for the bottom two income groups while for the top two groups displacement amount is about 2.8 liters.

Cost comparison

It is instructive to compare the cost of different alternative energy options for lighting, including kerosene lamps, SHS and grid-electricity among non-electrified households.

Cost of SHS per month is thus imputed using the compound interest rate method. Two assumptions are made namely, (1) all households living in non-elctrified villages are entitled to the micro-credit scheme and a cash subsidy, (2) the household choice of SHS depends on its level of income.

Estimated monthly cost of three lighting options show that, on average, the imputed monthly cost of SHS is about 5 times the cost of monthly spending on kerosene with a cash subsidy of $ 50 or $ 90. For the bottom two income groups, the monthly SHS cost is about 4 times the kerosene cost. It is about 6.4 times the kerosene spending for the top two income groups.
Average monthly cost of SHS is about 4 times the cost of grid-electricity

Assessing affordability

The cost of SHS is high relative to household incomes in rural Bangladesh. In 2002 the price of the most commonly installed SHS with a 40.50 Wp capacity was about $ 557 in Bangladesh. This is more than three times the rural household annual expenditure. Since major barrier for SHS adoption is the large upfront cost, micro-credit schemes can make, SHS to be an attractive option to many households in rural areas.

Taking the average energy budget among electrified households as a benchmark against which the affordability of SHS can be assessed. The estimated energy (Kerosene plus electricity) budget share among electrified households is about 2%. This is significantly lower than the budget share of about 8 for SHS based on the imputed monthly cost of SHS purchase.

For households living in non-electrified villages, grid-electrification is unlikely to be an option in near future. Thus, majority of households may have tendency to pay a substantial share of the budget for SHS. Probit model results show that the propensity to purchase SHS is very sensitive to household incomes. A 1% increase in per capita expenditure increases the probability of installing SHS by about 13%. A 1% increase in non-farm incomes increases the probability by about 10% holding other factors constant.

The criterion of a budget share of 7% is used to define affordability. Households are considered to be able to afford SHS if their budget share of monthly SHS financing is below 7%.

Spatial distribution of households who can afford SHS is also importants. It gives useful insights into the potential for cost reduction in SHS dissemination from economies of scale. Out of 50 districts in the sample, 16 districts have an affordability rate above 25%. The 16 districts also have relatively high concentration of households living in non- electrified villages at the level of 45% higher than the national average of 38%.

Conclusion

This paper presents propensity score-matching method that is able to yield accurate estimates of the treatment effect in nonexperimental settings in which the treated group differs substantially from the potential comparison units. The method is able to make the large comparison group down to the relevant comparisons without using information on outcomes Thus, it allows outcome data to be collected only for the relevant subset of comparison units. We can draw conclusion that it is extremely valuable to check the comparability of the treatment and comparison units in terms of pretreatment characteristics, which the researcher can check in most applications.

The propensity score method dramatically highlights the fact that most of the comparison units are very different from the treated units. Having discarded the irrelevant comparison units the choice of matching algorithm becomes important. We demonstrate that, when there are a sufficient number of relevant comparison units (in our application, when using the CPS), the nearest-match method does no worse than the matching without-replacement methods that would typically be applied. In situations in which there are very few relevant comparison matching with replacement fares better then the alternatives.

Policy Implications

Followings are the messages as emerged from the study findings. These can be taken into account by policy makers.

1. Widespread use of SHS can result in substantial reduction in carbon emission resulting from displacing kerosene by SHS.
2. In order to increase access to SHS, purchasing power of users needs to be enhanced through subsides, micro credits. Affordability of citizens is a concern.

3. More clarity is needed in the distribution system of SHS. Pro-poor venture needs to be ascertained.
4. Upfront costs burden can be lessened through proper and active participation of local level people in the form of voluntary organizations. This can be technical and physical cooperation in the early stage of SHS.
5. Motivational activities need to be strengthened so that knowledge and awareness of citizens are widened.

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