Rurality Forcing the Lights on: Is this worth it?

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Abstract

Energy shortage is a major concern in Nigeria. Albeit its abundance, fossil fuel is no viable solution considering varied pollution. Renewable energy technology like solar-powered-hub-for-homes is gaining prominence. The technology positions to address energy deficit in rural households but first, household decision makers' question of whether such investment is worth its cost demands answers. We assessed impact of this technology on wellbeing of adopting rural farming households in Nigeria and explored the drivers of its diffusion. Designing a Quasi-experiment, we randomly assigned 73 subscribers into treatment group and 219 non-electrified households into control group. Data were analysed using descriptive statistics, t-test, PSM, and probit regression. We found adoption increased wellbeing of adopters over non-adopters($p<0.05$) confirming our hypothesis that access to stand-alone solar-powered energy by off-grid rural households can potentially improve adopter's personal wellbeing. We found that household and remittance incomes, within-household school-aged children, payment flexibility, subsidy scheme, peer effect and pursuit of life's ease increased the probability of the technology adoption whereas increase in age, proximity to town and fossil fuel access negatively influenced its adoption ($p<0.05$). We recommended government subsidy on the technology. Diffusion may be aided by peer effect hence the recommendation to influence key individuals to adopt.

Keywords: Adoption, Electricity, Probit regression, Solar energy, Personal Wellbeing

JEL code: I310, O13, Q2

Introduction

Infrastructural decadence resulting from poor governance has thrown a considerable part of Nigeria into darkness. To offset the stymieing effect of power outage, many households have resorted to finding affordable and suitable small-scale decentralized power generation units for own consumption. Many households who have resorted to petroleum-fuelled power generating machines are gradually becoming aware of the attendant environmental sustainability issues. With increasing awareness of better alternatives in renewable energy, the use of solar powered energy sources is gradually being popularized in Nigeria, evident in the rising number of manufacturers and suppliers of solar powered energy hubs for individual homes. This is a more viable option for electrification given its relative affordability, ease of installation, and long-span usability however the question of whether its cost is commensurate to its benefits remains open especially for poor rural households with more competing basic needs.

We conjecture that adoption of this technology should impact on the wellbeing of the subscribing rural households. However, there is limited evidence to substantiate this position. In this study, we ask two questions. Firstly, how has adopting solar-powered energy hubs for homes impacted on the wellbeing of rural farming households in North Central Nigeria? Secondly, what are the drivers of solar-powered energy hub for homes' adoption in the study area? To the best of our knowledge, such micro-level research has not been carried out in Nigeria as majority of the research on renewable energy were attuned to potentials in renewable energy for power generation mostly in engineering fields.

Materials and Methods

Study area

The area we focused this research on is Kwara State, Nigeria, located between latitude 7° 20´ and 11°05´, longitude 2° 5´ and 6° 45` (Ogunlade et al., 2009). Kwara has a total population of about 2,371,089 million and covers a total land mass of 32,500 square kilometers out of which 75.3% is cultivable (National Population Commission [NPC], 2010). Kwara State is largely pre-dominated by rural dwellers, with some of these areas situated in remote physical location from the closest grid-connection point hence cutting them off the National Grid, while some that are fortunate to be on-grid have largely suffered power outage lasting years.

The Solar radiation map (from Hult et al., 2005) in Figure 2, reveals that Kwara ranks well above average in Nigeria, generating about 5500Wh/m^2 of solar radiation which is an indication that if properly harnessed, the energy crunch in the state will be ameliorated. The plethora of solar radiation in the state has endeared many rural farming households to adopt the technology given the ease of maintenance as well.

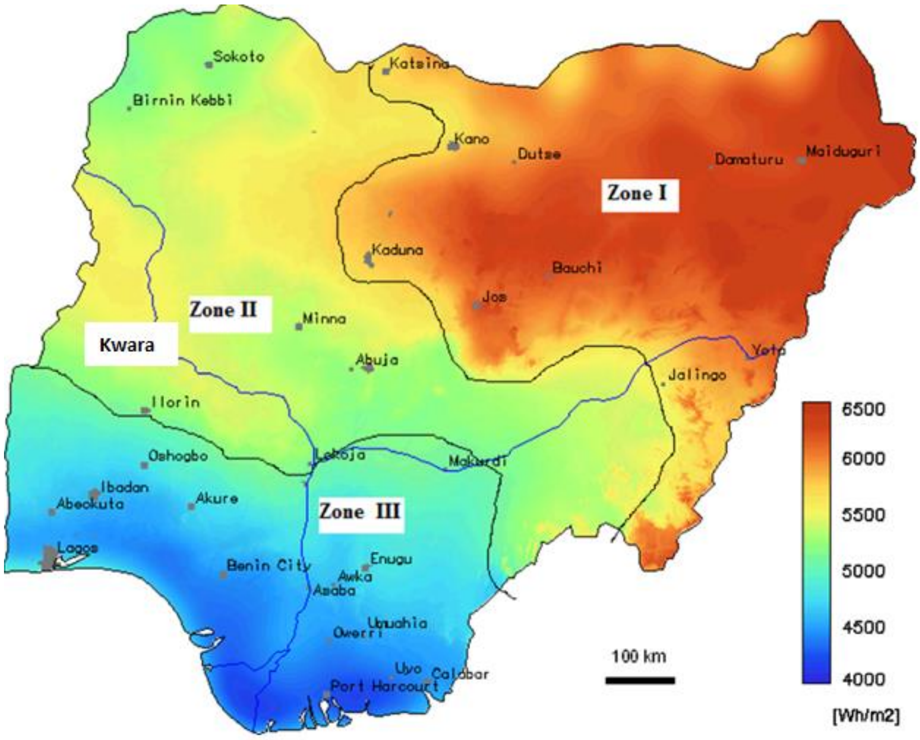

Figure 2: Solar Radiation Map of Nigeria (Huld et al., 2005)

Sampling Procedure

We conducted our study in Baruten, Kwara State Nigeria. The study area was purposively selected because majority of the rural areas in Local Government are off-grid while some are on-grid but have not had access to electricity in years. This study is a Quasi-experimental research designed to gain insight into the impact of adoption of Solar powered energy hub for homes on the wellbeing of rural farming households in Kwara State. The sampling frame from which the treatment group was selected is the household listing of subscribers who had adopted the solar powered energy hub for homes between January and March 2017, numbered at 243. Up to 154 of these households however generated power using fossil fuels as well hence selection precluded such households, reducing the frame for selection to 89 households. The Taro Yamane's sample size determination technique shown below was employed in calculating sample size (n) to be selected from the 89 households solely powered by the solar energy hub for homes.

$$n = \frac{N}{1 + N(e^2)}$$

Where N is the population size (89) and $\boldsymbol{e}$, the precision level (set at 0.05).

Based on this calculation, we randomly selected 73 subscribers into the treatment group in the Boria, Shiya, Kewu, Karoguru of Okuta District in Baruten Local Government Area. In order to have a control group for this experiment, 219 non-electrified households were randomly assigned from the Chikanda, Pomlo, Sinatokoru, Gobinkparu axis of Yashikera district in Baruten Local Government Area of the state. The sampling frame for the control group was the listing of households in the selected district. Due caution was taken to ensure completely non-electrified households were considered for the control group for two reasons which include firstly to remove upward bias that may be attributed to those that powered their homes with fossil fuels and secondly, to a reasonable extent, ascertain the similitude in the attributes of the control *viz-a-viz* treatment groups whilst avoiding spill-over effect. With this, one can ascertain the comparability of the treatment and control groups in terms of their pre-intervention characteristics.

We selected a total of 292 respondents for the study. With the use of a semi-structured questionnaire, we gathered primary data from these respondents. We gathered information on household socioeconomic characteristics, health-related expenditure, academic performance of relevant members, fuel expenditures, lighting hours, quality of lighting among others. Using data collected, we constructed a Personal Well-Being Index which is necessary in order to be able to measure wellbeing of the households. According to Stiglitz et al. (2009), a consensus is emerging that well-being is multi-dimensional. The framework we used modelled personal well-being as being constituted by observations in Table 1. The resulting index was consequently used to track the wellbeing of the respondent households.

(Table 1 Here)

Table 1: Constructed Wellbeing Index for respondent households

	Dimension	**Indicators**	**Weight**
1	Health	Frequency of occurrence of respiratory health-related ailments due to smoke inhalation for poor lightning sources	0.05
		Number of days lost to illness in a year	0.05
		Quality of lightning in the household	0.05
		General notion of health	0.05
2	Economic	Income from extended work hours attributable to access to light	0.05
		Fuel-related expenditure	0.05
		Respiratory health-related expenditure	0.05
		Cost savings given access to phone which otherwise could not be charged hence causing them to travel	0.05

3	Social	Increased recreational activities and time spent with family and friends after daylight Level of participation in group/communal discussion after daylight Increased access to information due to increased access to mobile phones.	0.05 0.05 0.05
4	Environmental	Ability to stay out of the way of harm from dangerous animals such as snakes, reptiles in the surrounding Reduction in indoor pollution and reduced risk of burns and indoor fires caused by other lighting sources such as kerosene, candles	0.05 0.05
5	Educational	Learning environment for school-aged children in the home given quality of lightning Performance of school-aged children in the household in the recent school term Number of after-school study hours	0.05 0.05 0.05
6	Psychological	Level of satisfaction with living conditions Level of satisfaction with health status Level of satisfaction with the local environment Level of satisfaction with interpersonal relationships	0.05 0.05 0.05 0.05
	Total		**1.00**

Author's Design

Analytical Techniques

We analysed the generated data using descriptive statistics, t-test, propensity score matching (PSM), and probit regression model. Firstly, we sought to ascertain comparability of the non-adopter and adopter groups through checking if the means of selected characteristics of both groups were normally distributed using the t-test statistic which is calculated as follows:

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{S^2{}_1}{n_1} + \frac{S^2{}_2}{n_2}}} \qquad \dots (i)$$

$\overline{X}_1$ = Mean of selected variable in non-adopters

$\overline{X}_2$ = Mean of selected variable in adopters
$S^2{}_1$ = Variance of selected variable in non-adopters
$S^2{}_2$ = Variance of selected variable in adopters
n_1 = sample size, non-adopters (219)
n_2 = sample size, adopters (73)

In examining the impact of adopting solar energy power hub for homes on the wellbeing of rural farming households, we used the propensity score matching. The method compared the wellbeing of adopters of the technology with their counterfactual non-adopter group. Our estimator is developed using propensity score matching analysis and 1:3 nearest neighbour matching algorithm was used to ascertain the average treatment test on the population as well as on the treated groups.

Propensity score matching (PSM) seeks to measure the effect of a policy, an intervention, or generally speaking, a treatment by accounting for covariates that predict receiving the intervention. PSM attempts to reduce bias arising from confounding variables that could be observed in an estimate of the treatment effect obtained from basically comparing the outcomes among individual units that got the treatment as against those that did not (Rosenbaum and Rubin, 1983). PSM engages a predicted probability of treatment against control group. This is based on observed predictors gotten from logistic regression which is then used to create a counterfactual group. The predicted propensity scores are used to measure the treatment effect. Following Becker and Ichino (2002), the widely used evaluation parameter of interest in the propensity score matching is Average Treatment Effect on Treated group (ATT) which may be stated as follows:

$$ATT = E(Y_1 - Y_0/P = 1) = E(Y_1/P = 1) - E(Y_0/P = 1) \quad \ldots \text{(ii)}$$

The propensity score gives the probability of adopting the solar power energy hub for homes by the rural farm household i, given a set $X = Xi$ of characteristics P(X) = Pr (P=1/X=Xi) (Pufahl and Weiss, 2009). The propensity scores are derived from the regression models in which these characteristics were compared. The impact of solar energy powered hub adoption on the adopters (causal effect of adopting solar energy hub for homes) was estimated by computing the differences across both groups:

$$ATT = \frac{1}{N_1}(Y_1 - Y_2) \qquad \ldots\ldots\ldots. \text{ (iii)}$$

where: ATT= Average impact of treatment on the treated; N_1 = number of matches (from regression model); Y_1 = average welfare index of solar energy hub for homes adopters; Y_o = average welfare index of solar energy hub for homes non-adopters. A positive (negative) value of ATT suggests that solar energy hub for homes adopters in the designed experiment have higher (lower) outcome variable than the non-adopters of the solar technology.

In order to examine the determinants of the solar energy hub for homes' adoption, the Probit model was fitted. The probit model predicts the probability of a household adopting the solar power energy hub for homes (i.e. dichotomous adoption decision, taking 1 if adopted and 0 otherwise). The dependent variable, y, depends on k observable variables x_k where k=1,…k. given a set of predictor variables. In terms of probability of occurrence, the Probit model may be given as follows:

$$Prob(y = 1) = \varphi\left[\sum_{k=1}^{k} \beta_k b_k\right] \qquad \dots\dots\dots \quad (iv)$$

Whereas, the probability of non-occurrence may be stated as:

$$Prob(y = 0) = 1 - \varphi\left[\sum_{k=1}^{k} \beta_k b_k\right] \qquad \dots.\dots\dots \ (v)$$

Where φ is the cumulative standard normal distribution function and β is the coefficient i.e effect of a unit change in a regressor x on quantile z, holding constant all other k−1 regressors while b are the modelled variables.

The household's decision to adopt the solar energy powered hub for homes is dependent on the criterion function stated as:

$$y^* = \gamma Z_i + U_i \qquad \dots\dots\dots.. (vi)$$

Where,
Y^* is the underlying index reflecting the difference between adopting and not adopting the technology, γ is the vector of parameters to be estimated
Z_i is the vector of the predictor variables explaining adopting Solar energy powered hub for homes, U_i is the normally distributed error term

It is important to note, however, that the concept of Y^* is unobservable in the real sense which necessitates defining Y_i which is a sort of shadow of the unobservable and may be defined as follows:

Y_i= 1 if Y_i^* > 0 (i.e adoption of the technology)
$Y_i = 0$ if otherwise (in this case non-adoption)

The model for estimating the probability of adoption of the solar energy powered hub for individual homes can be stated as:

$$P\left(Y_i = \frac{1}{X}\right) = \varphi(X\beta) = \int_{-\alpha}^{X\beta} \frac{1}{\sqrt{2\pi}}\ exp\left(\frac{-z^2}{z}\right) dz \qquad \dots\dots\dots. \ (vii)$$

Where,
P represents the probability that the ith household adopts the solar energy powered hub for individual homes
X equals K $\times$ 1 vector of the predictor variables
Z is the normally distributed standard variables $z \sim N(0, \delta^2)$
β equals K $\times$ 1 vector of the estimated coefficients

The probit model may be generally specified as:

$$Y_i^* = X_i\beta + \varepsilon_i \qquad \text{... ... ... (viii)}$$

$$Y_i = \begin{cases} 1 & if\ Y_i^* \geq 0 \\ 0 & if\ Y_i^* < 0 \end{cases}$$

Where, Y_i is the observed dichotomous endogenous variable, taking on the value 1 for adoption and 0 otherwise
Y_i^* is the underlying latent or unobservable variable which represents the adoption of the technology, X_i is the row vector of values of k regressors for the ith household, β equals the K $\times$ 1 vector of parameters to be estimated, while ε_i is the error term, satisfying the assumption that this is normally distributed.

Literature (Ugwu *et al.*, 2022, Ugwu *et al.*, 2021, IRENA, 2020, Mahesh 2020, Wordofa and Sassi,2017; Josephat and Likangaga,2015; Dewald and Truffer,2011 etc) were reviewed to establish variables that have been found to have influence on adoption of technology, in order to appropriately stylize our model. Variables modeled include awareness of the technology (dummy), age of household head (years), flexible payment plan (dummy), gender of household head (dummy), income (₦), number of school-aged children in the household (Count), proximity to city (Km), remittance income (₦), secondary occupation, years of schooling of household head (years), subsidy and rebate scheme(₦), peer effect (indexed), accessibility to fossil fuel (Km), pursuit of ease of life(indexed).

Results and Discussion

Table 2 presents a description of the socio-economic attributes of the rural farming households, delineated along adopters and non-adopters. The t-test results suggest that both groups have similar pre-intervention characteristics.

Table 2: Socio-economic attributes of the sampled households (n=292)

		Adopters (73)			Non-adopters(219)			
	Category	Freq.	Per cent	Mean	Freq.	Per cent	Mean	t-test stat [p value] Decision
Gender of household head	Male	52	71.23		148	67.58		
	Female	21	28.77		71	32.42		

Age of household head (years)	<40	24	32.88	48.30yrs	48	21.92	48.88yrs	0.448656 [0.6544] *f*
	40-49	32	43.84		65	29.68		
	50-59	12	16.44		63	28.77		
	≥60	5	6.85		43	19.63		
Marital Status	Single	14	19.18		38	17.35		
	Married	38	52.05		129	58.90		
	Divorced	7	9.59		16	7.31		
	Widowed	14	19.18		36	16.44		
Educ. Status	Primary education	39	53.42	5.64yrs	72	32.88	6.13yrs	0.93392 [0.3516] *f*
	Secondary education	18	24.66		69	31.51		
	Tertiary education	2	2.74		16	7.31		
	No formal education	14	19.18		62	28.31		
Monthly Income	<₦ 50,000	12	16.44	₦ 60,767.12	46	21.00	₦ 58,953.88	1.41344 [0.1595] *f*
	₦ 50,000 - ₦ 59,999	20	27.40		98	44.75		
	₦ 60,000 - ₦69,999	33	45.21		51	23.29		
	₦ 70,000 - ₦79,999	6	8.22		10	4.57		
	≥₦ 80,000	2	2.74		14	6.39		
Household Size	<5	11	15.07	8.30Ind.	45	20.55	7.59Ind.	1.17296 [0.2431] *f*
	5-9	43	58.90		136	62.10		
	10-14	14	19.18		19	8.68		
	>14	5	6.85		19	8.68		
Days lost to respiratory-related ailments of HH members	≤5	45	61.64	6.62days	56	25.57	11.68days	5.30589 [4.559e-007] *r*
	6-10	7	9.59		44	20.09		
	11-15	14	19.18		44	20.09		
	16-20	3	4.11		45	20.55		
	21-25	2	2.74		23	10.50		
	>25	2	2.74		7	3.20		
Remittance Income	Yes	32	43.84		79	36.07		
	No	41	56.16		140	63.93		
	Total	73	100.00		219	100.00		
Proximity to town	<50km	3	4.11	166.27km	3	1.37	167.52km	0.138306 [0.8903] *f*
	50km - 99km	14	19.18		26	11.87		
	100km - 149km	27	36.99		57	26.03		
	150km – 199km	9	12.33		48	21.92		
	>200km	20	27.40		85	38.81		

No. of Sch. Aged				4.95Ind.			4.27Ind	1.75497
children	<3	18	24.66		44	20.09		[0.08132]
	3-5	16	21.92		158	72.15		*f*
	6-8	24	32.88		10	4.57		
	>8	15	20.55		7	3.20		
Primary		45			151			
Occupation	Farming		61.64			68.95		
	Non-farming	28	38.36		68	31.05		

Field Survey
t-test decision to reject (*r*) or fail to reject (*f*) the null hypothesis H_0 = no significant difference in means of both groups at 0.05 level of significance

We found no significant difference in the means of age, years of education, household income, household size, proximity to town, and number of school-aged children in the adopter and non-adopter households. We failed to reject null hypothesis on the number of days lost to respiratory related ailments.

Most (69.41%) households were male-headed with mean age of 48.59years and married (55.48%). The household heads were sparsely educated with up to 72.6% and 61.19% of adopters and non-adopters respectively being either uneducated or having attained only primary education. However, the average years of schooling of 5.64 (adopters) and 6.13years (non-adopters) observed for the respondents are higher than the national average of 5.2 reported on UNDP's Human Development Reports. With about 8 individuals, average household size in the study area is larger than the national average of 5.9persons.

Households in the study area have between 4-5 school-aged children living in them. The non-adopter households have more incidences of related ailments than the adopter households (11.68 and 6.62days respectively). This result suggests that households that adopt cleaner energy may be less susceptible to respiratory related ailments. The average income in the study area was ₦60,767.12 and ₦58,953.88 for the adopting and non-adopting households respectively. Up to 56.16% and 63.93% of the adopting and non-adopting households respectively had no remittance incomes accruing to their household incomes.

Propensity Score Matching Analysis

Before carrying on the analysis for propensity score matching, we scrutinized the data for outliers. Since the dependent variable in our model is limited, we used the probit approach to estimate propensity scores. An underlining assumption in matching is conditional independence, requiring modelled variables to fulfil balance requirement. We assessed the differences in the propensity scores of the adopters and non-adopters using the pseudo R-squared test. When the covariates are randomly distributed across adopter and non-adopter groups, the value of the associated pseudo-R-squared is expected to be fairly low.

Table 3 presents a summary of the covariate balance showing the baseline means and variances in the adopters and non-adopters while Table 4 presents a summary of the standardized means and variance ratios in the raw and matched groups. Following Caliendo and Kopeinig (2005), we ascertained common support by comparing the variables minima and maxima. Propensity scores which lie outside these regions (either lower or higher) in the opposite group are usually discarded from the sample. From Table 4, an improvement could be seen in the scores after matching compared to before-matching.

Table 3: Baseline means and variances in adopters and non-adopters

Covariate balance summary

	Raw	Matched
Number of obs=	292	584
Treated obs =	73	292
Control obs =	219	292

	Means		**Variances**	
	Non-adopters	Adopters	Non-adopters	Adopters
Gender	1.493151	1.287671	0.2511	0.207763
Age of household head	21.88128	21.13699	111.8207	76.2032
Household size	17.52055	15.94521	34.02136	61.16362
Years of Schooling	6.136986	8.191781	18.55913	16.01826
Proximity to town	54.63927	62.57534	812.6629	813.7477
Remittance income	1.360731	1.561644	0.231662	0.24962
School-aged children	11.76712	13.60274	11.10607	25.8261
Secondary Occupation	1.497717	1.616438	0.251142	0.239726
Advertisement	1.410959	1.616438	0.243182	0.239726
Flexibility in payment	1.3379	1.60274	0.22475	0.24277

Table 4: Standardized differences and Variance ratio in raw and matched scores

Covariate balance summary

	Raw	Matched
Number of obs=	292	146
Treated obs =	73	73
Control obs =	219	73

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Gender	-0.428985	0.5147169	0.827411	2.474914
Age of household head	-0.076763	0.3109951	0.681477	1.23798
Household size	-0.2283525	-0.4497265	1.7978	2.504038
Years of Schooling	0.4941824	0.579592	0.863094	1.249337
Proximity to town	0.2782951	0.3746818	1.001335	1.425196
Remittance income	0.4095661	0.6066964	1.077517	1.239023
School-aged children	0.4271639	0.196603	2.325405	2.92858
Secondary Occupation	0.2396415	0.0970183	0.954546	0.963855
Advertisement	0.4181683	-0.0158857	0.985788	1.007963
Flexibility in payment	0.5477708	-0.1148201	1.08018	1.064698

Figure 3 presents the propensity scores' density before/after matching. Figure 3 depicts the similarity of the propensity score distributions after matching as well as the area of common support (Thoemmes, 2012). Figure 4 depicts propensity scores of raw and matched groups. Overlapping distribution of the propensity scores is observable in the treated and control groups suggesting the satisfaction of common support hence comparability.

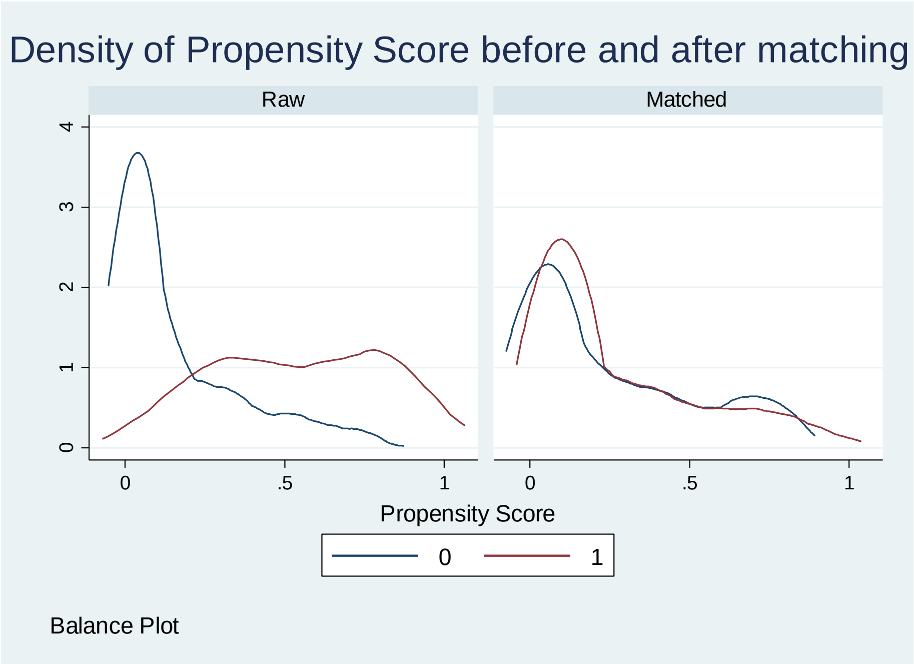

Figure 3: Density of Propensity Score

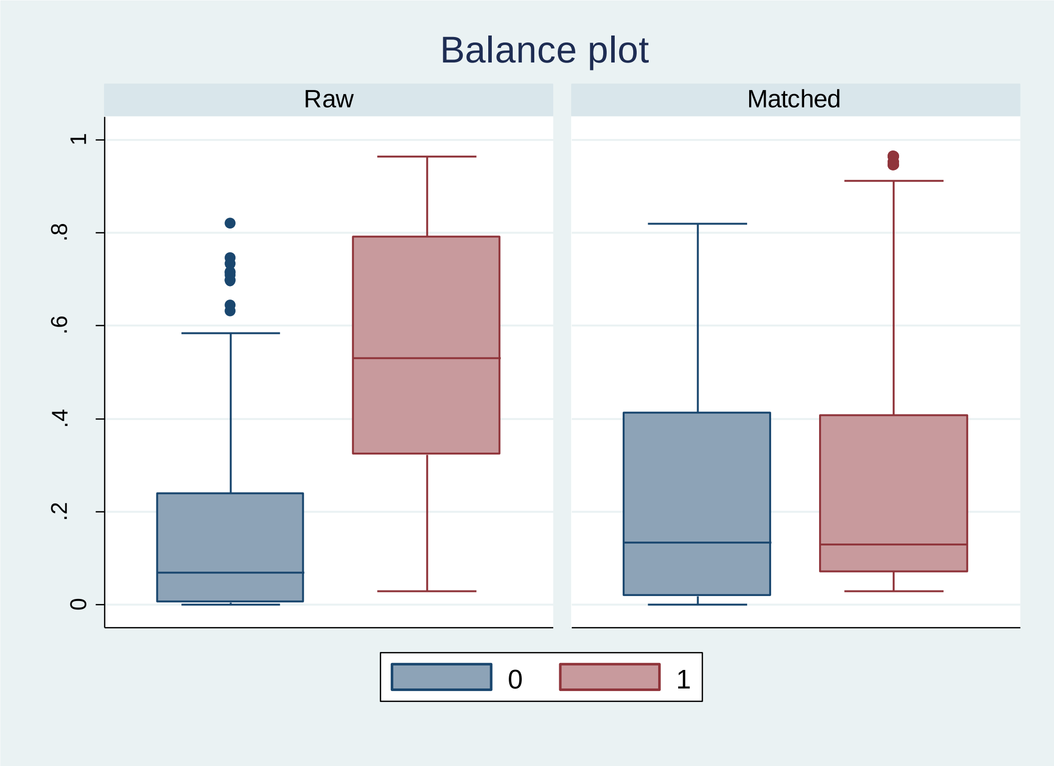

Figure 4: Balance Plot of Propensity Scores

Result of the average treatment effect on the treated (ATT) is as presented in Table 5.

Table 5: Average Treatment Effect on the Adopter Group

psmatch (welfindex) (adoptsol agehhhead gendr hhsize schyrs proximity childinsch secoccup adverts flexib, probit), atet nneighbor(3)

Treatment-effects estimation		**Number of obs =**	**292**
Estimator:	**propensity-score matching**	**Matches: requested =**	**3**
Outcome model:	**matching**	**min =**	**3**
Treatment model:	**probit**	**max =**	**5**

Welfindex	Coef.	AI Robust Std Error	z	P>|z|	95%Conf. Interval	
ATET						
Adoption of solar energy hub (1 vs 0)	8.709589	0.3926641	22.18	0.000	7.939982	9.479197

Average Treatment Effect on the adopter group presented in Table 5 shown that adopter households were better off in terms of wellbeing than non-adopters. We conclude that the well-being of individuals who adopted the solar energy power hub for homes generally increased with the treatment. These finding is consistent with apriori expectation. Okoro and Madueme, 2004, found that solar-generated energy has the potential for not only reducing road transport trips and consequently fuel consumption by the transport sector but also efficiently improving the internal communication system considerably. These, we believe, have multidimensional effect on the wellbeing of households for instance through improving their quality of life and cost savings on expenditure that would have otherwise reduced their wealth.

Kanagawa and Nakata (2008) submitted that access to modernistic energy like electricity will drastically improve the quality of life of those without it yet. Electrification can have positive outcomes basically through an increase in household time endowment considering the opportunity it bequeaths to households in extending their potential working day through artificial lightning (Salmon and Tanguy,2016). Our study agrees with findings of impact evaluation by Aklin et al (2017) that intervention succeeded in reducing kerosene expenditures and increasing the availability of electricity to considerable number of previously non-electrified households.

Study by Gustavsson (2007) in Zambia indicated a correlation between electricity access and educational, health as well as informational benefits to households. Hiremath et al. (2009) discovered that agricultural works/income generating activities in India could also be extended to night times given access to renewable energy technologies. Research by Howells et al. (2005) which examined the effects of energy use on the quality of life in rural Africa suggested that it served as a means to reducing local pollution while also allowing for special high value-added services. Findings from our research align with these researches because various indicators they examined constitute part of our wellbeing index.

Table 6 reports the results of the probit regression from which a pseudo R-squared which is the McFadden R-squared statistic is 0.45. With the log-likelihood of -89.86, the model can be adjudged to be of a good fit. Findings of the probit regression revealed that at 5% significance level, household income, remittance received by household, number of school-aged children in the household, flexibility in payment, subsidy scheme availability, peer effect and pursuit of life ease increased the probability of adopting solar energy power hub for homes in the study area. Increase in age, proximity to town and access to fossil fuels however decreased the probability of adoption.

On a study on renewable energy technology adoption and diffusion, Graziano (2014) found existence of spatial peer effect. Our study aligns to that, observing a unit increase in peer effect increases the probability of adoption by 0.539units. This is explainable as humans are social beings, having tendencies of being influenced by other’s decision. Janssen and Jager (2002) suggested the decision to install solar power can be characterized by high relevance of social compatibility, in that consumers frequently feel satisfied when consuming the same as their neighbours, often engaging in social comparison and imitation when making consumption decisions.

The roles of income as a determinant of adoption of this technology is unclear. Although income provides a socio-economic level that allows adoption decision to occur (Graziano and Gillingham,2014), it as well remains a clearly complex variable which can interact to dictate, in the first place, whether a particular household needs such technological intervention. Our study found a unit increase in household income increases the probability of adoption by 2.254e-05 which appears to be low, pointing to its ambiguity. This is in tandem with findings of Graziano (2014), where weak evidence was observed as to whether household income increase adoption.

Accessibility to fossil fuels by households decreased the probability of adoption of the technology by a factor of 0.0117. This supports the findings of Pohl and Mulder (2013) in a study which explored renewable energy technology diffusion in developing countries where it was found that high fossil fuel production delayed the diffusion of the technology in developing countries. The negative influence of proximity to town on adoption decision may as well be approached from the same perspective of viable options considering households that are closer to towns may have better alternatives to generate power and meet their needs for power, for example through traveling to the nearest town to carry out tasks requiring electricity (for example battery or phone charging).

Adoption decisions can be seen to be positively influenced by the number of school-aged children in the household at 5% level which is consistent with a priori expectation. It is expected that households with school-aged children are likely to be more interested in the technology since it will avail the pupils extended daylight which can be quite useful towards academic studies and related exercises. The role of information in adoption diffusion cannot be overemphasized as decision making is greatly influenced by an individual's awareness of the availability of such an option perhaps through advertisements. It can be seen that advertisement on the solar energy hub for individual homes increases the probability of its adoption by 0.3889 even though we did not find this to be significant, the positive sign is expected. This attests to the fact that creating awareness on the availability of such technology is pertinent to its diffusion.

We found that the probability of adoption of solar powered energy hub reduced with increasing age. This may be due to the fact that the younger people are more likely going to be receptive of such technology than the older generation who may have become more attuned to their old way of life. Remittance incomes to households could be seen to increase the probability of adopting the technology by 0.6998. This is expected as remittances can serve as a form of buffer beyond the limited household incomes on which basis households can then make such adoption decisions. Subsidy schemes on the solar energy powered hub for individual homes in the study area had a positive bearing on the probability of its adoption by a factor of 5.134e-05. Study by Winkler et al., 2018 in India, has shown correlation between subsidy and adoption of renewable energy which is as well consistent with our findings. We also found that individual's pursuit of ease in their way of life also influenced their decision to adopt.

Results of the probit regression indicated the probability to adopt increased by 0.106 with a unit increase in an individual's index of life ease pursuit. This is in line with a priori expectation given the various benefits attributable to the acquisition of such a technology by a household.

Table 6: Maximum Likelihood Estimates for the Predictor Variables in the Probit Model
Dependent Variable: Adoption of Solar energy hub for homes

Variable	*Coefficient*	*Std. Error*	*z*	*p-value*
Const	0.5409	0.7977	0.6780	0.4977
Gender	−0.4050	0.2330	−1.738	0.0822
Age	−0.0472***	0.0126	−3.740	0.0002
Household size	−0.0238	0.0249	−0.9551	0.3396
Years of schl	−0.0052	0.0288	−0.1794	0.8576
Household income	2.254e-05***	7.056e-06	3.195	0.0014
Proximity to town	−0.0033**	0.0017	−2.038	0.0416
Remittance	0.6998***	0.2374	2.948	0.0032
Sch aged children	0.2276***	0.0554	4.106	<0.0001
Sec occupation	0.1503	0.2507	0.5996	0.5487
Advert	0.3889	0.2623	1.483	0.1381
Flexibility in payt	0.7128***	0.2474	2.881	0.0040
Subsidy scheme	5.134e-05**	1.762e-05	2.9137	0.0481
Peer effect	0.0539**	0.04113	1.3105	0.0361
Access to fossil fuel	-0.0117**	0.0103	-1.1359	0.0452
Pursuit of life ease	0.0408**	0.0247	1.6518	0.0026

Mean dependent var	0.250859	S.D. dependent var	0.434254
McFadden R-squared	0.454233	Adjusted R-squared	0.374923
Log-likelihood	−89.45856	Akaike criterion	204.9171
Schwarz criterion	252.6703	Hannan-Quinn	224.0473

Conclusion and Policy Implication

We concluded that since adopting the solar energy powered hub for homes has indicated to generally increase the wellbeing of rural farming households, then efforts should be geared towards its diffusion. Given that the wellbeing of individuals aggregates and culminates into a peaceful and safer environment and ultimately improves the national wellbeing, it becomes important therefore to investigate the opportunities that abound in the generation of cleaner, cheaper and green energy from solar energy. We, therefore, recommend that government and policymakers should put in place interventions that will subsidize the cost of such technology hence making it more affordable to rural households that may be off the national grid or generally lacking in electricity supply.

It also becomes pertinent for distributors and marketers of this technology to extend their reach to hinterlands where people gain increased awareness on its availability and accessibility. An approach towards diffusing this technology may involve getting key individuals in each locality convinced on the benefits of the solar energy powered hub for homes. Subscription by such key individuals has ways of influencing peers to adopt in the vicinity as well. The relevance of this technology cannot be overemphasized in terms of nipping energy crunch in Nigeria in a cleaner, greener and more sustainable manner.

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