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The Impact of Biogas Technology on Rural Household Energy Needs: The Case of Adea Weredas, Oromia Region

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Abstract

Because of the domestic energy predicaments, rural households suffer disproportionately from the problems of ever deteriorating potentials of traditional fuels and the multiple adverse effects of its utilization mainly for cooking and lighting. The aim of this study was to examine the impact of biogas technology on household energy needs, in the case of Adea District, Central Ethiopia. The study emphasized and summarized the impact of domestic biogas on households' domestic energy needs mainly through the minimization of the multiple adverse impacts of the consumptions & the collection of inferior fuels for their domestic energy needs. The study employed a Quasi-Experimental approach using descriptive and inferential statistics for the analysis and interpretation of the study by the use of both qualitative and quantitative data. The study results showed that by using biogas energy, household's consumptions and expenses for fuel woods, cooking time & time taken for fuel collection; CH_4 *and* CO_2 *emissions decreased. The study also disclosed the existence of weak process evaluations, insufficient attention given to the human dimension of energy use, product development, and supply chain gaps which resulted in a high rate of non-functionality. Product development and marketing, strengthening process evaluation, and paying sufficient attention to the human dimension of energy use will sustain the utilization, maximize the benefits and proliferate its dissemination. Finally, the study tries to inform the concerned bodies to set up biogas energy initiatives and other stakeholders to have access to valuable data.*

Keywords: *Domestic energy, biogas energy, impacts of biogas technology*

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Introduction

While energy is not generally considered as a basic human need, the provision of adequate, reliable, and affordable energy is a precondition for meeting these needs. Having access to modern energy systems impacts human well-being by reducing health and safety risks associated with traditional energy use (Bruce et al., 2000; IEA, 2006), decreasing time and budget constraints on household members, particularly women and children, increasing labor productivity and income (ESMAP, 1996; IEA, 2002), and improving gender inequality and literacy (Cecelski and Elizabeth, 2000; ESMAP, 2004). Households generally use a combination of renewable energy and non-renewable energy sources that can be categorized as traditional biomass fuels (such as dung, agricultural residues, and fuel wood), intermediate fuels (such as charcoal and kerosene), or modern fuels (such as LPG, biogas, ethanol gel, plant oils, dimethyl ether, and electricity) for their domestic energy consumptions (ESMAP, 2004).

Domestic energy demand is the total amount of energy used in the house for household work such as heating, cooking, lighting, cooling, washing, and drying which may vary per household depending on the standard of living, the climate, the age, and the type of residence (World Energy Outlook, 2017). Households living in developing countries predominately rely on the traditional form of energy for their domestic energy needs whereas households in countries those become richer shift away from cooking exclusively with biomass using inefficient technologies (Smith et al., 2000).

The use of energy in traditional form is still the major source of domestic energy for developing countries, which is used by direct combustion, is not only inefficient but also imposes severe pressures on the household’s well-being and leads to energy poverty because of limited biomass resources. Domestic energy poverty refers to a situation where a household does not have access or cannot afford to have the basic energy for household work for daily living requirements. It can be also defined as the absence of sufficient choices for affordable, reliable, high-quality, safe and environmental benign energy services to support economic and human development (Reddy, 2000). When biomass resources are harvested unsustainably and energy conversion technologies are inefficient, there are serious adverse consequences on the health, valuable time, & economy of the households. Furthermore, the effort and time spent for collecting biomass fuels have been increasing throughout the developing world because of shortages caused by localized deforestation, increasing the energy demand of the household, and lack of ample supply-side interventions using alternate energy technology and clean, affordable renewable energy sources (IEA, 2015).

Despite the country's endowment with huge potentials of renewable energy sources, Ethiopia suffers from severe domestic energy problems and resources which have not yet been exploited to economically optimal levels. The country's domestic energy problem can be manifested by the relatively very low per capita energy consumption and the dominance of traditional biomass fuel use.

According to IEA (2015); in 2013, the per capita total primary energy supply in Ethiopia was merely 0.51 toe while it was 0.67 toe, 4.2 toes, and 1.9 toes for Africa, OECD countries, and the world average, respectively. Moreover, in 2009, the percentage of the population who relied on the traditional use of biomass fuels for cooking was 93 % in Ethiopia while it was 65 % for Africa, 77 % for Sub-Saharan Africa, and 39 % for the world as a whole (IEA, 2011). More depravedly, the demand for wood fuel far exceeds the sustainable supply in Ethiopia. According to Bekele (2013); in 2009, the demand for wood fuel was estimated to be 77 hm^3 whereas the sustainable supply was merely 9.3 hm^3. On the other hand; typical biomass fuels such as fuel wood, dung, or crop residues are burned in traditional stoves, which are highly inefficient, and time-consuming for cooking and the released gases are harmful to health and Environment.

In Ethiopia; different sizes and models of biogas technology dissemination had been started since 1979 as a project standalone approach (EREDPC and SNV, 2008). However, since 2008, fixed dome biogas technology has been disseminated in the country through institutionally structured programs aiming in contributing to the versatile benefits of the technology. The program launched in 2007 in four Regional States, namely Amhara, Oromia, SNNP, and Tigray Regions where a feasibility study was conducted. The study shows the potentiality for mass dissemination of domestic biogas technology ranging from 1.13 million from low scenario to high scenario 3.51 million households (Eshete et al., 2006). In the Oromia region; Adea Wereda was one of the two piloted Weredas for the demo phase for the Programme feasibility.

Research Gaps

Regardless of the potentiality of the country in general and the Regional in particular, the performance of the programme and the technology contributions were considerably below the expected targets and the switch from traditional fuel is not as the intended objectives. Therefore, assessing the impact of the technology on household domestic energy demand and filling the gap in sustainable rural livelihood energy demand interventions is a crucial area of research for the future programme up scaling, to safeguard the investment of the users, for the effectiveness of the Programme and sustaining the versatile benefits of the technology.

So far, a few researchers have been exploring various dimensions of household energy use in order to design and implement strategies not only to provide secure access to energy services but also to analyze the impact of energy investment on household energy needs. Apart from the 2007 Programme feasibility study, a few researches were done on the importance of the technology, design, and marketing of biogas technology including Bekele(2011) on technology design and system feasibility of biogas technology; Mengistu, Semane, Eshete, and Workneh(2016) conducted study on institutional factors affecting the dissemination of the technology in Ethiopia and Desalegn Z. (2014) conducted a study on the technology prospects of biogas technology and challenges for the uptake in Southern Ethiopia, Berhe et., al (2017) conducted study on biogas technology for sustainable energy supply for Africa. However, a yearly decrease in functionality rate exists both at the National and Regional levels was observed in the last five years. On the other hand, from the field report from Quality Management Team and the researcher’s observation; significant numbers of biogas owners were using dung cake and fuel woods for cooking even if the plant was functioning. To the best of the researcher’s knowledge, there is no impact evaluation conducted on the impact of the technology on a household's domestic energy needs using a Quasi-Experimental Method in the Propensity Score Matching Probit model.

Therefore; the study helps to investigate and evaluate comprehensive programme effectiveness with the intended goal and helps policy makers decide whether programs are generating intended effects. This can be done by filling gaps in understanding what works, what does not, and how measured changes in household energy needs are attributable to biogas programme or policy interventions. Besides; the evaluation targets a thorough understanding to what extent the biogas users still use inferior fuels and identifying the determinants for low functionality and production rate. Moreover; the evaluation is essential for identifying the bottleneck and to set counteractive strategic interventions for the programme effectiveness thereby prompting the switch from inferior fuels. Thus; this study aimed at filling this knowledge gap.

Literature Review

Household energy consumption in developing countries was about 1090 Mtoe in 2004, accounted for approximately 10% of the total world primary energy demand. Most of this energy is used for cooking, as well as heating and lighting (IEA, 2006). According to IEA (2006); energy demand in Africa has risen by half since 2000 though per-capita energy demand remains low at about one-third of the global average. The energy mix is dominated by biomass, which accounts for almost half of the energy demand across Africa and has a share as high as three-quarters of the total in sub-Saharan Africa and only one-third of the population of the continent has access to modern cooking fuels. Ethiopia is the second among top ten wood fuel-consuming countries in Africa next to Nigeria consuming 56,600 m3 which was 9.1% of total African Consumption.

Biogas, the mixture of gases generated from biodegradable resources in an anaerobic fermentation by methanogenic bacteria; has increasingly been utilized around the globe. It comprises 50 to 70 % of methane (combustible gas); 30 to 40 % carbon dioxide; 5 to 10 % hydrogen; 1 to 2 % nitrogen; 0.3 % water vapor, hydrogen sulfide, and other trace gases by volume (Lam and Heegde, 2011). The biogas produced (typically 60 percent of methane and 40 percent of CO2, along with traces of other gases) can be used as cooking fuel and to generate electricity, while the residue provides a rich fertilizer for crops.

Developed countries focus dominantly on large-scale biogas installations for combined heat and power generation whereas the primary focus of developing countries is on the construction of small-scale biogas digesters that particularly generate heat for cooking (Ghimire, P.C., 2013).). Concerning developing countries, China outstandingly leads the world in the number of domestic biogas plants to provide domestic sanitation and off-grid energy and to modernize agriculture (WHO, 2011). By the end of 2010, the total number of domestic biogas installations reached 40 million from which the country produced 15,400 hm^3 biogas annually (Dong, 2012).

With the potentiality to serve up two million households, biogas technology has been promoted since 1979 in order to help overcoming the increasing energy crises in Ethiopia (PID, 2007). A feasibility study carried out revealed that of 600 to 700 domestic biogas plants in Ethiopia, about 60 percent had stopped functioning due to a range of problems; including water and technical problems, dung shortage, evacuation, and loss of interests (Eshete, Sonder, and Heedge, 2006). Another source also installations of all types constructed up to the establishment of NBPE was approximately 1000 (EREDPC and SNV, 2008). Despite past failures, there was a renewed interest in biogas technology so the National Biogas Programme Ethiopia (NBPE) initiated to develop a viable and sustainable commercial biogas sector (EREDPC and SNV Ethiopia, 2008; PID, 2007). The programme primarily set to address the energy demand of rural households thereby establishing sustainable and commercially viable biogas technology, resulting in the reduction of biomass fuel consumption for domestic energy purpose and significant improvement of emission reduction, fuel expenses, and fuel collection time.

Based on the three-dimensional energy profile framework, a new method of identifying household energy transitions are not limited to switching between fuels, stacking multiple fuels, or adopting improved cook stoves. Instead, they include all three dimensions of household energy systems. The three-dimensional energy profile model provides a holistic view of household energy system characteristics and the shifts that occur due to changes in any of three dimensions of the household energy system (i.e. energy service demand, energy carrier, energy conversion technology). According to Wilhite et al., 2001, the three-dimensional model is a representation of the "social appropriation" of energy use along with the increasing use of a more efficient and modern energy system.

Research Methods

A mixed research design (both qualitative and quantitative) was used to gain a comprehensive view of the Programs effectiveness and for various specific research questions and hypotheses. It examined to what extent biogas technology affected inferior fuel consumption, and inferior fuel expenses, to what extent the intervention affects low-grade fuel collection time, cooking time and emission of CH_4 and CO_2. Besides; the study also examined what factors affecting the energy needs using the technology, what and how different causes interact or influenced by quantifying the relationship between the predictors and dependents variables based on careful observations, measurement, and interpretations of the objective reality. Based on the state of the problem and nature of the research question; Quasi-Experimental Research methods were used. In this case; observations and analyses of the situations were conducted without intervention (non-interventional research in which the independent variable is not manipulated) was used for quantitative research design. The survey questionnaire was used as data instrumentation (collection technique) as it permits clarification of questions, a higher responsive rate, suitable for both literates and illiterates.

It helps to know the existence, nature, and magnitude of the problem (hard evidences) and to address potential statistical bias in the biogas program impacts. Furthermore, case study and KIG were used for a qualitative study to generate information that may be critical for understanding the mechanisms through which the program helps beneficiaries. Both descriptive and inferential statistical methods were used for data analysis.

The sample universe was biogas users and non-biogas users. The sample universe was distributed in 20 of the 26 rural Kebeles found in the Wereda in all directions and they were highly clustered nearby the town of Bishoftu. The samples of the controls were collected from two peripheral Kebeles of the Wereda.

According to the 2017 biogas inventory, only 88 (22 biogas plants of size 6 m^3, 57 biogas plants of size 8 m^3, and 9 biogas plants of size 10 m^3) biogas plants were functioning. In order to have a better result for quantitative analysis; all the eligible 88 functioning biogas plants were considered for quantitative analysis and the rest 152 were not functioning and therefore used to characterize the causes of non-functionality with purposive sampling method to select non-biogas user sample households. The data inputs for study were gathered both from primary and secondary sources. Primary data was collected using a survey of the personal interview which was carried out in a semi-structured way using a set of predetermined questions and standard techniques of recording which was conducted from February 22, 2018, to March 24, 2018. Propensity Score Matching is also used for addressing the objective stated above.

Results and Discussions

Descriptive Analysis

On average, the cattle size of treated respondents and control respondents were found to be 8.56 and 8.58 statistically significant at 1 % ($p<0.01$). Among 88 biogas users, 22(25%) of biogas users have a cattle size below the required standard during the time of the study (cattle size below 5) which significantly affects the feeding volume, especially for larger sizes. Assuming the average daily volume of dung obtained from a single adult cow was 10kg and nearly 60% of the dung was collected for open grazing cattle (PID), the quantity of the dung was below the expected standard with the existing cattle size. The problem caused insufficient or no daily gas production for the household's energy needs. As the daily gas production decreases, the user stops feeding so that it caused high non-functionality rate which was even unfortunate for restoring and maintaining its functionality.

Table 1

Number of Selected Biogas Users Having Cattle Size Below the Required Size

Size of the plant in m^3	Frequency	The average number of cattle existed during the installation	The average number of cattle that existed during the time of the study	Expected feeding volume in Kg.	Existed dung volume during the study period in Kg.
10	1	7	4	80-100	24-40
8	14	5.21	3	60-80	18-30
6	7	4.285	3	40-60	18-30
Total	22				

Source: Own Survey, 2018

The treated groups had a mean family size of 5.8 and the control groups had a mean family size of 5.33. Both groups had a minimum family size of 1 and the maximum family size of 12 and 13. The units in the two groups were statistically significant at 5% with both groups didn't have statistically mean differences. However, the mean family sizes of both groups were higher than the Regional average which is 4.78 (CSA, 2007). This was due to the definition stated in the survey questionnaire for the purpose of biogas energy consumption at the individual level and population increase in ten years laps‟ time. Similarly, on average, the farm size of treated respondents and control respondents were 3.1 and 2.9 statistically significant at 5%. The average size of the farm size was greater than the Wereda average (2hectare) because biogas users were economically better off farmers.

Of the total respondent household heads, 70% of them were able to write and read with a formal education background and the remaining 30% were illiterate. The result shows that the chi-square value was 3.95 statistically not significant at 1 %($p>0.01$.) Of the total respondent of household heads, 34% of them were beneficiaries of credit services whereas the rest 66% were not. The result shows that the chi-square value was 4.01 statistically significant at 5% ($p<0.05$.) Of the respondent household heads, 70% were male-headed and 30 % were female-headed with a chi-square value of 3.75 statistically not significant at 1 %($p>0.01$). The significant difference is due to the fact that biogas was installed for the family level and the household name is designated under male household members because of cultural reasons.

Table 2

Two-Sample t-Test and Chi2 Test for Independent Variables.

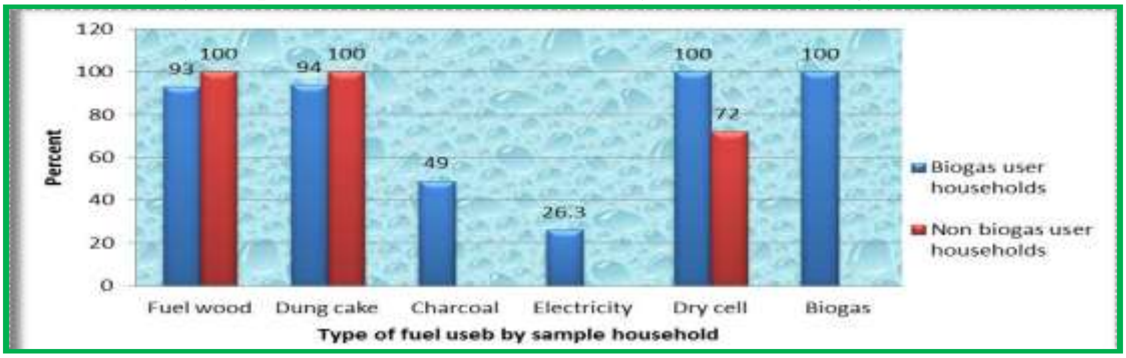
Continuous Variable	Participants					Non-participants					t-value
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	
Cattles	88	8.56	6.2	0	50	80	5.88	5.23	0	28	-3.0309*
Farm size	88	3.13	4.06	0	33	80	2.98	2.16	0	11	-0.4253**
Family size	88	5.85	2.23	1	12	80	5.33	2.52	1	13	-1.4248*
Education	88	6.11	4.75	0	17	80	2.43	3.63	0	16	-5.6164*

Source: - Analysis Result

About 94% of the respondent biogas users also responded they either prepared or collected the dung cake from farmyard. Dung cake was also sold with sacks as fuel wood mostly sold as unit of bundles of donkey back. 94% of biogas users were using dung cake, 92% were using fuel wood, 49% were using charcoal, and 26.3% were using electricity. Nevertheless; all non-biogas users were using fuel wood and dung cake for their domestic energy needs. This implies household biogas users had more access to electricity than those non-biogas users. Non-biogas user households were not using charcoal for their domestic energy demand as they had access to traditional fuels from nearby areas or forests. Moreover, even if there was no switch off from inferior fuels; biogas users substantially differ in the type of fuel utilization for their domestic energy demand while non-biogas users are confined mainly to fuel wood and dung cake for cooking or lighting purposes.

Figure 1

Composition of Sample Household's Utilization Of Domestic Energy Sources



Source: Own Survey

Impact Estimation Results

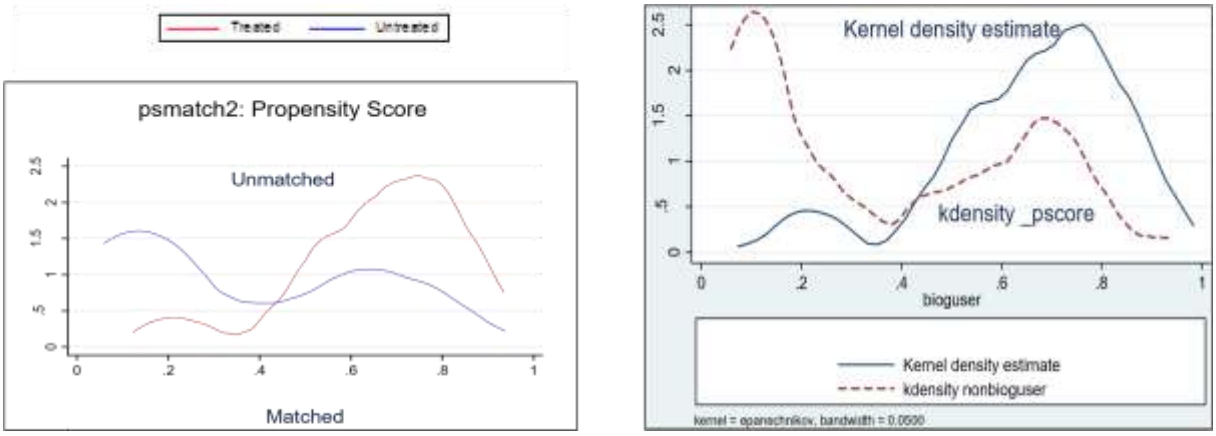
The pseudo-R^2 value 0.2384 (See annex 1**)** implies that the low pseudo-R^2 value shows that the selected treated and control group households do not have many differences in overall observed characteristics. Thus; it became easy to find a good much between participant and non-participant households. A binary probit model was used to estimate the PSM for participation. The treated household to the programme with its treatment variables takes the value of 1 if treated and the nonparticipants take the value of 0. For propensity score estimation; the PSM considered different observed characteristics of the participants such as demographic characteristics such as education status & educational level of the households and economic factors such as cattle size, farm size, and credit status of the households were used for the estimation.

Distribution of Propensity Score before Matching

The distribution of the households with respect to the estimated propensity score based on the model as indicated in figure 2 shows both groups considered a wider area in the distribution of propensity score. As the propensity score is a probability, it has to be in the interval [0; 1].

Figure 2

Distribution of Estimated Propensity Score Before Matching



Source: Own Survey

With respect to the estimated propensity score distribution, most of the treatment and control groups are found in the middle. Partly, fewer distributions of the propensity score of the control groups were found on the far-left side whereas fewer distributions of the propensity score of the treated households were found on the right side of the distribution. Almost all the observations of the treated and control group characteristics (covariates) were within the range of common support so that adequate match of similar propensity score exists with sufficient overlap.

Defining the region of Common Support and Balancing Test

After estimating propensity score, imposing common support conditional on propensity score distribution of the household with or without the programme is important. Testing of the balancing property is that observations with the same propensity score must have the same distribution of observable characteristics independent of treatment status (conditional independence). The optimal number of blocks was 5 ensures that the mean propensity score was not different for treated and controls in each block. The numbers of both groups for each block in the inferior bound were 88 and 54 respectively. The estimated PS mean and median in the region of common support were 0.5942 and 0.64062629. The average probability of participation in the BPE for all respondents was 52.4% which is fairly high.

Testing the balancing of PS was satisfied. To make a reasonable comparison, a sizeable region of common support ranging in the interval [0.12287736, 0.93471422] was selected. Observations which fall outside the inferior bound (0.12287736) and the upper bound (0.93471422) were off-support and therefore discarded from the region. Thus, the overlap assumption assured the treatment observations need comparison observations "nearby" in the propensity score distribution 0<P(Ti=1/Xi) <1. That is discarding the treatment for which the PS for each possible value of the vector X not within the unit interval was maintained.

Table 3

Region of Common Support

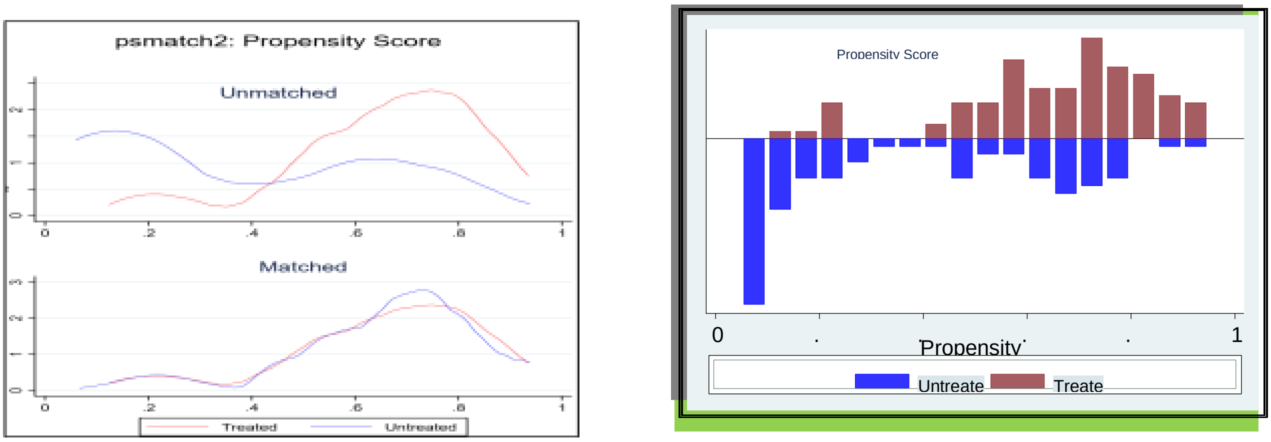
psmatch2: Treatment assignment	Common support (fuel wood consumption)		Common support (fuel wood expenses)		Common support (fuel collection time)		Common support (Cooking time)	
	Off support	On support	Off support	On support	Off support	On support	Off support	On support
Untreated	0	80	0	80	0	80	0	80
Treated	0	88	0	88	0	88	0	88
Total	0	168	0	168	0	168	0	168

The inferior bound, the number of treated and the number of controls for each block after balancing	Biogas Programme participation		
	0	1	Total
.1228774	10	2	12
.2	10	5	15
.4	10	23	33
.6	23	38	61
.8	1	20	21
Total	54	88	142

Source: Own Survey,

Each treated unit is matched only with a control unit whose propensity score falls into a predefined common support region of the propensity score matching. As we can observe from figures 13 & 14; after matching, because of sufficient overlap on the common support region, almost all the treated and non-treated groups were matched.

Figure 3**:** PS Distribution Graph after matching and PS Graph on the region of common support



Source: Own Survey

Choice of matching algorism and ATT estimation

The main purpose of PSM is balancing two non-equivalent groups under observed covariates in order to estimate the accurate effect of a treatment on which the two groups are different (Luellen et al., 2005). PSM constructs matched data to have the similarity between treated & control groups. By this procedure, selection bias can be removed through randomized matching of similar control variables where the selected variables are not systematically different from the others. To select and conclude a matching algorism estimator; balancing all explanatory variables with the lowest pseudo R^2 value or a large matched sample size is most suitable. To estimate the average treatment effect and to show the robustness of the result obtained; four matching algorism estimators were conducted. The common matching algorisms includes Nearest Neighbor Matching (attnd), Kernel Matching (attk), Radius or Caliper Matching (attr) and Stratification Matching (atts)(Khandker et al. 2010).

Table 4 summarizes the impact estimation results of the intervention (BPE) in the outcome variables with four matching algorism which shows there is a positive significance of the programme. As indicated, control individuals participated in the nearest neighbor matching, kernel, radius, and stratification matching algorisms in the same order for ATT estimation fuel wood consummation of the household per year in bundle. The PSM result tells as that on the average; the participation to the BPE was going to have significant impact in reducing the fuel wood consumption by 100.17 bundles using nearest neighbor, 92.67 bundles using kernel, 82.65 bundles using radius and 99.47 bundles using stratification matching than non-biogas user households at 1% probability level with t-values of -8.763, -11.018, -10.512 & -7.813 in the same order. The study chooses radius matching (all the control matched in all the outcome variables) as large matched sample size is preferable and balancing test is equally mean.

Table 4

Average Treatment Using Matching Algorism

Matching Algorisms for:	n.treat.	n.contr.	ATT	Std. Err.	t
Fuel Wood consumption					
Nearest neighbor(attnd)	88	28	-100.17	11.432	-8.763*
Kernel Matching(attk)	88	54	-92.675	8.411	-11.018*
Radius matching (attr)	88	80	-82.654	7.863	-10.512*
Stratification method (atts)	88	54	-99.478	12.733	-7.813*
***Fuel Wood* Expenses**					
Nearest neighbor(attnd)	88	28	-3373.9	491.295	-6.867*
Kernel Matching(attk)	88	54	-3073.8	377.878	-8.135*
Radius matching (attr)	88	80	-2673.0	362.201	-7.380*
Stratification method (atts)	88	54	-3345.9	404.761	-8.267*
Fuel collection Time					
Nearest neighbor(attnd)	88	28	-16.080	7.484	-2.149*
Kernel Matching(attk)	88	54	-14.524	5.084	-2.857*
Radius matching (attr)	88	80	-16.386	4.963	-3.302*
Stratification method (atts)	88	54	-8.685	7.226	-1.202*
Cooking Time					
Nearest neighbor(attnd)	88	28	-31.477	3.863	-8.148*
Kernel Matching(attk)	88	54	-32.103	2.992	-10.730*
Radius matching (attr)	88	80	-30.323	1.829	-16.576*
Stratification method (atts)	88	54	-31.238	1.999	-15.627*

Source: Own Survey

Similarly, the PSM result tells as participation in the Biogas Programme Ethiopia has a positive impact in reducing inferior fuel time collection in minutes per round trip by 16.08 using nearest neighbor, 14.52 using kernel, 16.38 using radius, and 8.685 using stratification matching than the control group at 1% probability level with t-values of -2.149, -2.857, -3.302 & -1.202 in the same order. The PSM result also tells us that the programme participation decreases the fuel wood expense in Birr per year by 2,673.0 and cooking time in a minute in a single cooking by 30.323 using radius matching statistically significant at 1% with t- values 7.380 and 16.576 values in the same order.

Test for the balance of Covariates and propensity Score

Balancing test was undertaken to check whether the distribution of the treated and the control group average propensity score and mean of X were similar or balanced. Therefore, after the propensity score was estimated and the region of common support was observed; the balancing property was checked if ^P(X/T=1) ~^P(X/T=0). The balanced score protecting the committed standard errors affecting the confidence interval (95%, p>.05) which holds 0<p(x) <1 was maintained. The choice of the observables such as the education status of the household satisfied and the condition anticipates the drawing of causal inferences from these data without making strong external assumptions involving model-based extrapolation. Test methods like the mean standard bias reduction for the matched and unmatched respondents, and equality of the means of unmatched and matched respondents using t-test and chi-square test for joint significance of the use the variables were used to ensure the balancing power of the estimation (matching quality).

Table 5

Test for the balance of Covariates and Propensity Score

Variable	Unmatched Matched	Mean		%bias bias	% reduct	t-test		V(T)/ V(C)
		Treated	Control			T	p>t	
Credit	U	.40909	.2625	31.2		2.02	0.045	.
	M	.3625	.29149	15.1	51.6	0.95	0.341	.
Education status	U	.90909	.4625	109.1		7.15	0.000	.
	M	.9	.91729	-4.2	96.1	-0.38	0.706	.
Education level	U	6.1136	2.425	87.3		5.62	0.000	1.71*
	M	5.4	5.2204	4.3	95.1	0.28	0.780	1.22
Cattle size	U	8.5682	5.875	47.0		3.03	0.003	1.41
	M	8.4	9.2786	-15.3	67.4	-0.83	0.410	0.79
Farm size	U	3.129	2.9125	6.7		0.43	0.671	3.53*
	M	3.129	3.3736	-7.5	-13.0	-0.49	0.622	3.24*
* if variance ratio outside [0.66; 1.53] for U and [0.66; 1.53] for M								

***Source**: Own Survey, 2018*

From the above table, the mean standard bias, the percentage standardized bias, and the percentage of bias reduction are indicated for each observable before and after matching. The standard bias before matching is in the range of 0 to 170.9% in the absolute result. On the other hand; the standard bias after matching was in the range of 2.9% to 15.4 % in the absolute result which is well below the critical value suggested by Rosenbaum and Rubin (1983) which is 20%. Therefore; the process of balancing created a high degree of match between the treatment and control groups and the t-values of all the covariates between the two groups after matching are statistically insignificant (less than t-tabulated) whereas three of the five covariates were statistically significant before matching. Thus, by the matching, the differences between the treatment group and non-treatment group were reduced considerably, and the hypothesis that the mean values of the two groups do not differ after matching holds for the covariates.

Test for the Robustness of Average Treatment Effect:

One approach to check the robustness of the finding is to estimate Propensity score equation and then use the different matching methods previously used to compare the result. In this case, the findings with different matching techniques are quite consistent. Another way to check the robustness is applying direct nearest-neighbor matching instead of estimating the propensity score equation. The results were again consistent with earlier findings and the positive impact of participation was seen at 1% significant level. As depicted in table 5; the robust result indicates the reduction of fuel wood consumption by 99.41 bundles of fuel wood and expenses of fuel wood by Birr 3,343.24 per year per household. Similarly; the cooking time was also decreased by 30.88 minutes per single cooking time significant at 1% level. The fuel collection time was decreased by 12.56 minutes per round trip but was statistically insignificant at 1% level.

Table 5

Test for Robustness of ATT

Outcome variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
FWQAN						
SATT	-99.41	11.49	-8.65	0.000	-121.9311	-76.8870
FWEXP						
SATT	-3,343.24	544.46	-6.14	0.000	-4,410.35	-2,276.13
Ttimefuelc~n						
SATT	-12.56	6.83	-1.84	0.066	-25.94315	0.829512
TTimecooki~w						
SATT	-30.88	2.989	-10.33	0.000	-36.73793	-25.02343

Source: Own Survey

The predicted probability for each person that the individual receives the treatment (propensity score) for the treatment and control groups are similar in various ways except the treatment effect on the means of dependent variables (fuel saving, fuel expense & fuel collection time) observed on the treatment group. This effect (ATT) has then to be redefined as the mean difference of average treatment effect on the treated for those treated falling within the range of common support level. Using nearest neighbor matching; the result on average treatment effect on the treated shows that participation in the biogas programme causes the reduction of fuel wood consumption quantity by 96.63 bundles per annul, fuel wood expense of Birr 3,232.10 per annual, decreases the time for collecting inferior fuels per a round trip and cooking time per single cooking by 16.76 minutes and 30.63 minutes in the same order statistically significant at 1%.

Table 7

Average Treatment Effect of the Treated

Variable	Sample	Treated	Controls	Difference	S.E.	T stat
FWquantCu	Unmatched	63.21	138.85	-75.65	7.65	-9
	ATT	63.21	159.84	-96.630	11.80	-8
ExpfwCu	Unmatched	3161.31	5554	-2392.69	359.38	-6
	ATT	3,161.31	6,393.41	-3232.10	505.08	-6
timefuelcollec~n	Unmatched	111.98	128.75	-16.761	4.7105	-3
	ATT	111.98	128.75	-16.7613	7.61	-2
TTimecookingfw	Unmatched	29.431	59.1875	-29.75	1.57	-18
	ATT	29.431	60.056	-30.625	4.14	-7

Source: Own survey

Test for the Joint Significance

As indicated in table 8, the low value of pseudo R2 and the insignificant likelihood ratio (LR) tests supports the hypothesis that both groups had the same distribution of the covariates after matching. According to Rosenbuam and Rubin (1985), the standardized bias before and after matching and the mean bias should be less than 5%.

Table 8

Joint Significance Test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.238	55.44	0.000	56.3	47.0	126.9*	0.40*	67
Matched	0.003	0.68	0.984	4.7	3.6	12.4	1.16	33

Notes: * if B>25%, R outside [0.5; 2]
Source: Own survey

The test result signifies that the mean bias is 4.7 which was less than 5% indicating there is insignificant mean difference between the two groups and the assumption B = 12 % < 25%, R= 1.16 inside [0.5; 2] was maintained. This result indicated that the matching procedure was able to balance the characteristics in the comparison groups. All the tests depicted suggest that the average treatment on the treated can be estimated based on the chosen matching algorism and available data set.

Sensitivity Analysis

Propensity scores are obtained from observational data that lack randomization and it is clear that matching estimators are not robust against the hidden biases. Matching is only controlling for the difference observed variables and there may be some bias resulting from the unobserved covariates that could affect subjects receive treatment or not (Luellen etal., 2005). Since it is possible to estimate the magnitude of selection bias whether it changes the inference about the treatment effect with non-experimental data, the problem can be addressed by sensitivity analysis.

As per Hujer et al. (2004), sensitivity analysis for insignificant effect is not meaningful. Sensitivity analysis provides a method to assess how robust/healthy findings are from hidden bias assuming all the relevant covariance are employed in the treatment assignment.

Estimation-based PSM is unbiased if there are no unmeasured confounders (hidden covariates) and if all the relevant covariates are incorporated in the model. If there are unobserved variables that affect the assignment into treatment and the outcome variable simultaneously, a hidden bias may arise to which matching estimators are not robust (Becker & Caliendo, 2007).

In sensitivity analysis, before matching, the sample households were assigned to the unknown probability that the treatment or the control groups are independent. In a randomized experiment, everyone has the same chance to be benefited from the interventions and r is therefore r=1. If r=3; an observational study may be one subject triple as likely to receive the treatment because of unobserved pretreatment difference. By varying the sensitivity parameter gamma from 1 to a maximum given by gamma = 3 in increment of 0.05; the corresponding value of the different sensitivity parameters and each outcome variables in the upper bound p-value of Rosenbaum Sensitivity Test for Wilcoxon‟s signed rank test, if a bias of magnitude r=3; it should have the different significant at 0.05 level (Rosenbaum, 2015)

As per the result of outcome variables; we have seen that for increase of 3 in Γ, the upper bound significance level for fuel wood consumption, fuel wood expenses, fuel collection time and cooking time was 4.5e-11, 4.5e-11, 1.6e-11 and 2.0e-1 which are well below the usual 0.05 threshold. That is, no odds of the outcomes of the programme intervention because of different values on an unobserved covariate despite being identical on the matched covariates which change our inference.

Conclusions and Recommendations

The use of biogas helps to reduce the energy consumption of household by 29,900 MJ and 5,401 MJ from fuel wood and dung cake in the same order per year per household. Similarly; biogas user household able to reduce fuel wood consumption quantity by 96.63 bundles per annul on average statistically significant at 1%. Hence, the provision of clean and convenient cooking fuel to the households at their door-step significantly contributes to combat the effect on the ecological environment due households‟ domestic energy need. Thus, biogas users are less likely to consume inferior fuels for their domestic energy needs than non-biogas users.

Household biogas users on average able to save the expenditure to fuel wood by Birr 3,232.10 per annual. This will have a positive impact on households' net income as long as the plant is functioning. Educational status, educational level, cattle size and access to credit have also significant ($p<0.01$) positive influence on fuel wood consumption, expenses, and fuel collection time. Correspondingly, biogas users are also more likely save money for the expenditure of inferior fuels than non-biogas users and therefore generate more income than non-biogas users.

Household biogas users reduces the drudgery by decreasing the consumption of inferior fuel and thus saves time for the collection of fuel wood by a quarter an hour (16.76‟) per round trip on average statistically significant at 1%. The difference is not as large as the benefit of the technology for cooking is limited to the cooking culture of the households so biogas users still tend to search for inferior fuels. Similarly, biogas decreases the cooking time by half an hour (30.63‟) statistically significant at 1%. The time saved to collect fuel wood and cooking time by the use of biogas helps rural household's biogas users to perform other productive works. This can be possible by replacing the time for rural women to collect or purchase inferior fuels over more than 20 years (Service life of the product).

The largest share and the main root cause of non-functionality were non-technical problems (problems of feeding and user dissatisfaction) which accounts for 27% of the non-functionality rate. Besides nearly 86% of those non-functional biogas owners were convinced by the information obtained from house-to-house product-based promotion. Limited understanding of the drivers of energy use and transition, including overemphasizing the product benefit as the main drive of energy choice and use impairs the end use of energy. Explicitly; paying insufficient attention to the human dimension of energy use or problems affects the use of energy and energy technology. Biogas users are more likely better adopt and use the technology by obtaining genuine, explicit, and specific problem-based product dissemination than the product benefits like cooking and lighting itself which affects user's expectations from cultural and technological perspectives with its clear and explicit benefits.

Plant size as a technological attribute determines the daily gas demand of the household. The functionality of installed biogas plants increases with a decrease in the size of the plants. Small-size biogas plants are more likely properly managed, feed, and used by biogas owners for their domestic energy needs. Currently, 63% and 65% of biogas plants with the size of $8m^3$ and $10m^3$ non –functioning. As population size increases, pasture land decreases pasture land decreases which finally lead to a decrease in cattle size & volume of substrate for feeding. This results in the imbalance between the household daily gas demand and the daily gas production which leads to non-functionality due to non-satisfaction to its benefit.

Most biogas owners in Wereda are still switching to inferior fuels for their energy demand because of the relative benefit from factors of technological attribution. 94% of biogas users use dung cake, 92% use fuel wood, and 49% use charcoal. It is found that there is no sizable significant change on dung cake consumption. This implies biogas users are still using similar quantities of dung cake for baking rather than feeding the plant and the switching of biogas owners to such traditional fuel is significantly fortified and the non-functionality rate upsurges. This is due to the household's endogenous behavioral and cultural factors such as cooking practices, life style, and social status. The household in the study area regularly uses a common dish known as Injera (a flat pan cake like food) which shares more than half of the household's domestic energy needs. Because they have no other alternative energy sources to bake Injera, biogas users use dung cake and fuel wood for baking Injera and heating cheese for which biogas still doesn't resolve the problem. Above all, had there been a biogas Injera stove with Sinidu Model domestic biogas technology, the use of inferior fuels could have been reduced in a significant amount as baking Injera consumes a significant amount of household energy.

The dissemination of the technology should be focused on smaller size biogas plants rather than large sizes to prepare the required amount of substrate to feed the proposed size. As alternative; identifying, selecting, and prioritizing where the benefit of the technology is feasible for the longer term where there is enough grazing land, relatively far from off-grid, and enough water available is fundamental for maintaining functionality rate.

Innovation can bring revolutionary results with radical performance characteristics of the technology. The programme should do on technology push (R &D) on product development and benefit maximization of the technology mainly on Injera stove. The innovations of the biogas Injera stove have a rebounding effect due to the increased use of energy services mainly for baking and the greater efficiency of the product. Since baking consumes more energy; to save more biogas energy for cooking; the Programme should complement solar cells for lighting and other benefits. This can be possible through the programme incentivizing mechanism or making a bilateral agreement between the solar suppliers and the Programme to apprehend the diverse household energy needs and to sustain the benefit of the technology as targeted.

The Programme should re-enforce the process evaluation for sustaining the benefit of the technology and to restore functionality as the majority of the technical problems. These includes gas line problem due to a lack of follow-up (after sales services), lack of accessories and lamp sets (supply chain), and lack of timely operation and maintenance services. Hence; it needs further investigation on the biogas stove emission test to precisely determine emission reduction not only from manure management and methane combustion but also the degree of the technology efficiency in emission reduction. Besides, the fuel-saving from cooking using biogas can be further investigated more using efficiency and saving tests (WBT and CCT) to get more reliable results in the laboratory.

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