Adoption of Biogas Energy Technology and Its Socio-Economic Impact: Evidence from Northern Ethiopia

Muuz Hadush [1*], Kidanemariam Gebregziabher [2], Serkalem Dejen[3]

[1]Assistant Professor Department of Economics; Mekelle University, P. O. Box 451 Tigrai, Ethiopia. Email: muuz.hadush@mu.edu.et, ;* Corresponding author
[2]Associate Professor, Department of Economics; Mekelle University, P. O. Box 451 Tigrai, Ethiopia. Email: kidane.gebregziabher@mu.edu.et ;
[3] Ph.D. student, Department of Economics; Mekelle University, P. O. Box 451 Tigrai, Ethiopia. Email; serkea16@gmail.com

Abstract

The paper is motivated to identify factors that affect household biogas adoption decisions, the intensity and extent of biogas adoption, and its impact on biomass energy consumption and medical expenditure. To this end, data was collected from a sample of 200 households that were randomly selected using a multistage sampling technique. Logistic regression for the adoption decision and propensity score matching to evaluate the impact of adoption on the amount of biomass energy consumption and medical expenditure were used. The propensity score matching result showed that biogas technology adoption has an impact on medical expenses and biomass energy consumption. The average treatment effect results of the study revealed that households with biogas technology do spend less money on medication and have lower biomass consumption compared to non-adopters.

Key words: Adoption; Biogas Technology; PSM, Household; Biomass energy

1.Introduction

In the past half century, a series of conferences have been convened with poverty reduction as a central agenda. One possible explanation for this seemingly contradictory phenomenon is the low or slow improvement of technologies, amid the proliferation of improved technologies in most developing countries, especially in rural areas (Serote et al., 2023). Hence, unless development intervention properly targets the rural poor and is effectively supported by the adoption of improved rural technologies, no poverty reduction aspiration or declaration will materialize.

Improved rural technologies, following Rogers (2003), are defined to include equipment (such as biogas energy technology in our case), genetic material (improved varieties of animals as well as crops), farming techniques, and agricultural inputs that have been developed to improve the effectiveness of agriculture and processes. The technology to be introduced needs to be not only effective and productive but also sustainable. Sustainable technologies reduce negative effects on the environment by reducing or preventing pollution, reducing resource consumption (e.g., raw materials, energy), or using less polluting or energy-intensive materials (CELAC, 2017). The focus of our paper is that access to modern energy sources is one of the critical factors that affects the quality of human life (Legros et al., 2009). Despite the important role of access to modern energy sources and the high attention given to the sector by governments, the progress made to get national electricity energy supply to the majority of the population in developing countries, especially in rural areas, has remained very limited (Amigun et al., 2012).

Approximately 1.06 billion people (about 14% of the global population) lived without electricity as of 2016, about 125 million fewer people than in 2014 (Renewable Energy Policy Network for the 21st Century, 2014). About 2.8 billion people (38% of the global population and about 50% of the population in developing countries) live without clean cooking facilities (D'Adamo, 2018). The vast majority of people without access to either electricity or clean cooking are in sub-Saharan Africa or the Asia-Pacific region, and most of them live in rural areas. For example, 55% and 41% of the people without electricity access live in sub-Saharan Africa and Asia-Pacific region respectively. Moreover, 67% of people without access to clean cooking facilities live in the Asia-Pacific region, and 30% live in sub-Saharan Africa (D'Adamo, 2018). Hence, because of the shortage and limited access to commercial modern energy and the current economic situations in most African countries, despite its adverse environmental impact, biomass has remained and is expected to be a dominant energy source for years to come (Amigun *et al*., 2012).

Ethiopia, being one of the least developed countries in Sub-Saharan Africa, suffers from a severe domestic energy problem, and the country's domestic energy problem can be manifested by the relatively low access to electricity (51% (2020), though better than the Sub-Saharan 48.2% (World Development Indicator, 2020). The scarcity of wood fuel and associated problems are more severe in northern Ethiopia, where most of the forests were lost and nearly all available areas have been converted into cultivation and pasture lands. For instance, in the Tigrai and Amhara regions, dung fuel accounts for about 22.8% and 20.4% of the total domestic energy consumption, respectively (Damte et al., 2012).

However, since the last decade, due emphasis has been given to the development of the energy sector, and intervention efforts have already started to show some promising results. One of the crucial areas of intervention in the energy sector is the development and dissemination of biogas technology. The Ethiopian government decided to subsidize bio-digesters in rural households in an effort to provide a substitute for firewood, charcoal, dried animal dung, and other biomass materials (Kamp and Forn, 2016).

Biogas plants use locally available raw materials, and the gas obtained from them can be used for cooking and lighting activities. In addition to energy services, biogas plants also provide benefits like time savings for fuel collection, improving health and sanitation, acting as a source of the best organic fertilizer, and in general helping to conserve the environment (Mshandete and Parawira, 2009).The use of biogas technology has numerous health and social benefits. The health benefits include, among others, a reduction in smoke-borne diseases such as headache, eye burning, eye infection, and respiratory organ infection. Moreover, biogas adoption improves households' sanitation via toilet connection with biodigesters, the absence of sooths and ashes in the kitchen, and a reduction in burning accidents. Biogas saves time for social activities; it improves social status in the community; it lessens women's and children's work burden; and it offers brighter light that assists children to study during the night and is expected to contribute to the quality of education (Ghimire et al., 2015).

Recently, the Ethiopian Ministry of Water and Energy has developed a strategic plan for the mass dissemination of domestic biogas plants in various parts of the country. The National Biogas Program (NBP) was implemented to test the feasibility of biogas in actual farm settings. During the program's first phase, the government disseminated 14,000 bio-digesters across four regional states: Tigrai, SNNP (Southern Nations, Nationalities, and Peoples), Oromia, and Amhara (Mengistu et al., 2016). Therefore, this research tried to address the adoption decision, extent, and rate of biogas adoption and its impact on the socio-economic benefits it has resulted on households in one of the project districts in Tigrai region, northern Ethiopia.

The contribution of this study is twofold. First using hypothetical measures of time and risk preferences, this is the first study in East Africa and particularly in Ethiopia to show time and risk preferences as key factors influencing biogas technology adoption on top of conventional factors. The inclusion of these factors distinguishes this paper from previous studies, which explicitly focused on only socio-economic and demographic factors. Second, policymakers will be able to gain adequate knowledge from both the findings of adoption and the impact evaluation on how to promote and disseminate information regarding this technology in the region. Tigrai is an interesting case for the purpose of this study.

2. Literature review

Given the stagnant agricultural productivity and persistent food insecurity in low-income countries—notably in sub-Saharan Africa (SSA)—there has been continued interest in the adoption of new technology and its impact on productivity. In particular, how to increase maize yield and sustain its yield gain are major issues for agricultural development in SSA. Such interests are supported by changes in favor of the adoption of new agricultural technologies. It includes the release of improved crop varieties and the widespread use of mobile phones, which is expected to reduce transaction costs (Aker, 2011); and the buoyant use of microcredit and index-based weather insurance, which would help remove cash constraints and excessive exposure to production risks (Magruder, 2018).

In fact, there are signs of the Green Revolution in maize and rice in SSA, reflected in sharply increasing yield trends in the advanced regions of Africa (Otsuka and Muraoka, 2017). A widely observed puzzling phenomenon in SSA is the low adoption rate of seemingly profitable technology (Sheahan and Barrett, 2017). The first major question that the literature on technology adoption ought to ask is whether truly productive and profitable technologies are available in the SSA and other low-income countries. The related question is what the appropriate agricultural technologies are that can bring about significant and sustainable improvement in productivity in the region (Ruzzante et al., 2021).

The literature falls into three paradigms: the innovation-diffusion paradigm; the economic constraints paradigm; and the adopter-perception paradigm (Prager & Posthumus, 2010). Each paradigm emphasizes the role of different factors in adoption rates and patterns. The innovation-diffusion paradigm assumes that information is the critical parameter that controls the spread of an innovation through a society. This paradigm follows from the pioneering work of Ryan and Gross (1943), while Rogers (2003), first published in 1962, remains a seminal work that defined the field of innovation diffusion research. This field focuses on the characteristics of innovations and how they influence rates of diffusion. Societies are assumed to be composed of a range 'of adopter categories, from innovators and early adopters to laggards, which differ on measurable socioeconomic, personality, and communication attributes (Rogers, 2003). Innovation-diffusion theory has been criticized for assuming that innovations will be appropriate, which Rogers (2003) refers to as 'pro-innovation bias.

The economic constraints paradigm postulates that farmers aim to maximize utility and that uneven resource endowments lead to observed patterns of adoption (Adesina & Zinnah, 1993). In comparison to the innovation-diffusion paradigm, the economic constraints model emphasizes the role of economic factors at the individual level in determining adoption decisions. However, this model allows for only strictly rational and informed behavior and fails to capture the effects of cultural and individual perceptions of an innovation. The adopter-perception paradigm allows for

a level of subjectivity by contending that it is the perceived need to innovate and the perceived attributes of innovations that determine adoption behavior (Adesina & Zinnah, 1993).
The characteristics of an innovation and its delivery combine with cultural, contextual, and individual factors to influence perception (Adesina & Zinnah, 1993; Prager & Posthumus, 2010). Dhehibi (2020) presents an analytical model of decision-making that includes the intrinsic factors of knowledge, perceptions, and attitudes, which are conditioned by extrinsic factors such as the characteristics of the farmer, the external environment, and innovation. Within the adopter-perception paradigm, farmers can be considered rational actors who maximize utility; however, in contrast to the economic constraint's paradigm, the definition of utility is expanded beyond simple financial considerations.
Hence, our paper's contribution rests on the following facts: To the best of our knowledge, we did not come across such a contribution. This is perhaps the first study in East Africa and particularly in Ethiopia to show time and risk preferences as key factors influencing biogas technology adoption on top of conventional factors. Second, the availability of secondary data enables us to calculate the rate and extent of use. Third, policymakers will be able to gain adequate knowledge from both the findings of adoption and the impact evaluation on how to promote and disseminate information regarding this technology in the region. Tigrai is an interesting case for the purpose of this study. From a practical and policy perspective, it is relevant to understand how farmers decide and use this technology.

3. Data and Method

3.1 Description of Data and Study Area

The study was conducted in Tigrai, northern Ethiopia. In order to select respondents, the study used multistage sampling techniques. In the first stage, three villages were selected purposefully based on the availability of biogas technology. In the second stage, the population of the selected villages was stratified into two groups: adopters and non-adopters of the biogas energy technology. Then, a total of 200 samples consisting of 88 adopters and 112 non-adopter respondents were randomly selected from the three villages in proportion to the size of the household in each village. To collect the socio-economic data, a semi-structured questionnaire was administered. Experimental design questions were also included in order to elicit the risk, loss, and time preferences of respondents.

The result from the descriptive statistics is presented in Table 1. Referring to Table 1, the observable dependent variable Y_1 in equation (2) take a value of 1 if the farmer adopts biogas technologies, and 0 otherwise. The results indicated that 56% of a total of 200 rural farmers were adopters of biogas and 44% were non-adopters during the study period. The adoption rate is very low throughout the country due to the rising cost of installation and lack of awareness (Marie et al., 2021; Kamp & Forn, 2016). Depending on the location and season, the construction cost of biogas plants fluctuates. However, the average price of a single biogas plant is estimated to be ETB 13,000 (USD 582.7) for a 6m3gas plant, ETB 13,500 (USD 605.1) for an 8 m3 gas plant, and ETB 14,000 (USD 627.5) for a 10 m3 biogas plant(Marie et al., 2021). 50% of the initial cost subsidy was provided by the Ethiopian National Biogas Programme (NBPE) to biogas users to compensate, encourage users, and improve the affordability of the biogas plants (Kamp & Forn, 2016), implying that the cost of installment is shared by the household and the government itself. The average age of adopters and non-adopters was 43.85 and 50.09 years, respectively, which implies that there was a significant age difference between adopters and non-adopters. Adopters on average have more than 6.2 family sizes as compared to non-adopters (4.5), with an average size of 5.36 members in the study area. Biogas users owned a herd size of 5.8 TLU units, while non-users of biogas owned about 3.2 TLU units, with a mean of 4.5 units. The average farm size is 0.5 ha for users as compared to 0.4 ha for non-users.

On average, farmers using biogas spend 37.33 minutes more than non-users, who only spend 45.40 minutes per day to travel to the nearest market. Adopters of biogas are seemingly better off than non-adopters in terms of farm income. On the planting of trees, the average planted tree is not statistically different between the two groups, but non-adopting farmers have slightly higher (238) values compared with the value of adopters (200). In this study, male-headed households represent about 80.5%. Among male farmers, 78.6% are non-adopters, and 83% are adopters.

Table 1: Descriptive Statistics

Variable name	Adopters(88)		Non adopters(120)		t-test value
	Mean	Std.Dev.	Mean	Std.Dev.	
Age(year)	43.852	7.0605	50.098	11.848	4.3715***
Family size(unit)	6.2386	1.4699	4.4910	1.4205	-8.5048***
Cattle holding(unit)	5.8522	3.3443	3.1964	2.9495	-5.9581***
Farm size(hectare)	0.4659	0.1616	0.4143	0.2151	-1.8733
Market distance(minutes)	37.329	12.009	45.402	12.176	4.6820**
Farm Income(ETB)	16500	13737	9216.7	7884.5	-4.7113
Planed Tree(number)	199.79	230.40	238.17	239.82	1.1428
Risk averse(safe choice)	3.5795	1.5816	4.6964	1.2840	5.3762*
Loss averse (safe choice)	5.0454	1.3382	5.9375	1.0159	5.3588**
Sex (Female=1)	0.1704		0.2142		0.6031
Marital status(Married=1)	0.7954		0.5803		10.393**
Water Source(available=)	0.6363		0.2589		28.728***
Electric connection(Grid=1)	0.0340		0.2857		21.611***
Technical assistance(Yes=1)	0.7386		0.3750		26.194**
Patient(Early choice in both)	0.2613		0.0625		15.285*

Source: Own survey, 2019

Of the farmers contacted, the proportion of impatient farmers is higher (85%) than patient farmers, which is 15%, of which 73.87% are impatient farmers who adopt biogas while 93.75% are impatient farmers who decide not to adopt the technology. Biogas users had a significantly higher marital status (79.54%) than that of non-users (58.03%). Biogas users have reliable and sufficient water sources, on average 2.5 times higher than those of non-users. Moreover, 82.5% of the farmers reported not having access to grid electricity, of which 96.6% were found to be biogas users. Adopters on average experience more than twice (1.96%) as many technical labor skills as compared to non-adopters in the study.

3.2. Hypothetical Experimental Design

The instrument we employed in this paper instead is similar to the approach of Noussair et al. (2013) and Drouvelis and Jamison (2012), asking respondents to directly compare declining present choices with constant future choices. A simple hypothetical risk elicitation instrument was

presented to our respondents using a similar approach to Noussair et al. (2013) and Drouvelis Jamison (2012), who measured risk aversion by counting the number of safe choices made by the individual in five and seven list choices, respectively.
In order to elicit risk preferences, participants were shown a table with seven rows and asked to choose between a safe option and a lottery option in each row, where the safe option is held constant in each row, but the amount in the lottery option increases from row to row. More precisely, first-row subjects choose to receive 60 ETB with certainty, or they choose to play the lottery and have a 50 percent chance of receiving 0 ETB and a 50 percent chance of receiving 110 ETB. The amount in the lottery row increases from 110 ETB to 120, 130, 140, 160, 180, and 200 ETB. Our measure of individual risk-aversion is the number of instances in which a respondent chose a certain row. Thus, our risk aversion measure ranges from the lowest possible value of 0 to the highest possible value of 7. Then respondents revealed their risk preferences by switching from option 1 to option 2.
A choice of zero safe option out of seven choices indicates a risk-loving individual, and a risk-neutral individual would make either one or two safe choices out of the seven choices, and more than two safe choices indicate risk aversion. More safe choices indicate greater risk aversion. Consulting the work of Drouvelis and Jamison (2012) as a measure of loss aversion, we used the frequency with which a subject chose the safe option.
In order to test whether heterogeneity in individual time preferences affects biogas technology adoption, we measure individual time preferences using a hypothetical question (Ashraf et al., 2006) to link the state of impatience to biogas adoption. In this case, individuals under two consecutive questions were initially asked to make a choice between having one chicken now or two chickens at the end of this year (would you like to have one chicken now or two chickens at the end of this year). In the second stage, we presented individuals with the same question but changed the two chickens into three chickens (would you like to have one chicken now or three chickens at the end of this year?). Depending on the individual's response, we classify individuals as patient for those who prefer to wait and always choose the future reward (two or three chickens) in both cases or impatient for those who always want the immediate benefit (one chicken).
Results from Table 1 revealed that the mean risk aversion of user farmers appears to be 3.57 as compared to the mean value of 4.69 for non-user households, which is almost statistically different at 10%. We also find that the average loss aversion is 5.04 for user farmers and 5.93 for non-users in risk field experiments, suggesting that adopting farmers in general are less risk-takers and loss-averse in the study area.

3.3 Econometrics model specification

To analyze the collected data both simple descriptive and inferential statistics were used. While the binary probit model was estimated and applied so as to analyze the adoption decision of Biogas energy technology, the propensity score matching (PSM) was used to evaluate the impact of adoption on medical expense and biomass consumption based on the strong assumption of conditional independence. The net benefit obtained from adopting biogas energy technology is denoted by the latent variable, y^* which is assumed to be a continuous variable that we do not observe and is determined by the model as follows:

$$y^* = x\beta + e \quad (1)$$

Where x and β are vectors of observed explanatory variables and parameters including a constant respectively. The model is shortly represented by the scalar index $x\beta$ which ranges from the value zero to one. The residual term e is assumed to be uncorrelated with x i.e. x is not endogenous (Wooldridge, 2010). While we do not observe y, we actually observe whether or not the individual farmer made a decision to adopt the biogas energy based on the following discrete choice rule:

$$y=1 \text{ if } y^* > 0$$
$$y=0 \text{ if } y^* \leq 0 \quad (2)$$

Since we do not have data on y* we cannot estimate the model (2) with OLS as usual. Instead, we can estimate parameters of interest using probits and logits traditionally viewed as suitable models when the dependent variable is not fully observed (Wooldridge, 2010). Following this, the probability that a 'positive' choice is made (e.g. adopting, as distinct from not adopting, a biogas technology) is modeled as:

$$\Pr(y = 1|x) = \Pr(y^* > 0 \mid x),$$
$$\Pr(y = 1|x) = \Pr(e > -x\beta) \quad (3)$$

This expression produces the logit model, $\Lambda(x\beta)$ if e follows a logistic distribution, and the probit model, $\phi(x\beta)$ if e is follows a standard normal distribution as:

$$\Pr(y = 1|x) = \Lambda(x\beta)$$
$$\Pr(y = 1|x) = \phi(x\beta) \quad (4)$$

According to Wooldridge (2010), the principle is that Probit and logit models are estimated by means of Maximum Likelihood (ML). Assuming that the probability of observing y_i = 1 is G(xβ) and the probability of observing y_i = 0 is 1-(xβ), the probability of observing the entire sample when l refers to the observations for which y = 1 and m to the observations for which y = 0. is given by

$$\mathcal{L}(y|x;\beta) = \prod_{i \epsilon l} \mathrm{G}(x_i\beta) + \prod_{j \epsilon m} [1 - \mathrm{G}(x_i\beta)] \quad (5)$$

From the previous expression, we have seen that we get G(xβ) when y = 1 and 1-(xβ) when y = 0. The expression in equation (5) can be rewritten as

$$\mathcal{L}(y|x;\beta) = \prod_{i \epsilon l}^{N} \mathrm{G}(x_i\beta)^{y_i} + \prod_{j \epsilon m}^{N} [1 - (x_i\beta)\,]^{1-y_i} \quad (6)$$

From this expression, we can produce the log likelihood for the sample is by converting equation (6) in to log likelihood function

$$\ln \mathcal{L}(y|x;\beta) = \sum_{i=1}^{N} \{y_i \ln \mathrm{G}(x_i\beta) + (1 - y_i) \ln[1 - (x_i\beta)\,]\} \quad (7)$$

Considering G as the logistic CDF, then we obtain the logit log likelihood by maximizing log likelihood function

$$\ln \mathcal{L}(y|x;\beta) = \sum_{i=1}^{N} \{y_i \ln \Lambda\mathrm{G}(x_i\beta) + (1 - y_i) \ln[1 - \Lambda(x_i\beta)\,]\} \quad (8)$$

Which yields the final shape of logit log likelihood function

$$\ln \mathcal{L}(y|x;\beta) = \sum_{i=1}^{N} \left\{ y_i \ln\left(\frac{exp(x_i\beta)}{1-exp(x_i\beta)}\right) + (1-y_i)\ln\left(\frac{1}{1-exp(x_i\beta)}\right) \right\} (9)$$

and probit log likelihood function if G follows standard normal CDF

$$\ln \mathcal{L}(y|x;\beta) = \sum_{i=1}^{N} \{ y_i \ln \Phi\mathrm{G}(x_i\beta) + (1-y_i)\ln[1-\Phi(x_i\beta)\,]\}\,(10)$$

In most cases the main interest is to examine the effects on the response probability $\Pr(y=1|x)$a s a result of a change in one of the explanatory variables, the partial effect of explanatory variables sayx_j on $\Pr(y=1|x)$is obtained from the partial derivative as follows:

$$\frac{\partial \Pr(y=1|x)}{\partial x_j} = \frac{\partial \mathrm{G}(x_i\beta)}{\partial x_j}\,(11)$$

In the case of a discrete variable, we evaluate the effect on the response probability depending on all the values of the other explanatory variables and the values of all the other coefficients. Determining whether the effect is positive or not is known according to the sign of the coefficient. Thus, our interpretation in this paper basically results from this marginal effect calculation (Wooldridge, 2010).

In order to estimate the impact of biogas energy adoption on biomass energy consumption, we used propensity score matching (PSM) based on a strong assumption of conditional independence. Here, we assume that the adoption or treatment effect is based on observable characteristics such as the size of cattle or dry matter around the homestead. Implicitly, the PSM method assumes selection of the treatment is based on observable characteristics only and hence unobserved characteristics should not affect the biogas technology adoption (Rosenbaum and Rubin, 1983). The impact evaluation is done by matching biogas technology adopters with non-adopters according to their propensity score using PSM techniques and the average difference was computed. Households who adopt biogas technologies were compared to those who would not own/adopt. In reality, we can’t observe both states at the same time; individuals are either in the treated or untreated states. That is we observe

$$Y_i = D_i + D_i Y_{1i} + (1-D_i)Y_{0i}$$

$$y_i = \begin{cases} y_{1i}, & if D_i = 1 \\ y_{0i}, & if D_i = 0 \end{cases} \quad (12)$$

Where Y_{1i} indicates for users and "Y_{0i} for none users and D=1 indicates for an individual being treated D=0 otherwise. For matching to be valid, the primary assumption underlying matching estimators is the Conditional Independence Assumption (CIA) which states that conditional on the set of observable characteristics of X, the non-treated outcomes are independent of treatment status $(Y_{1i}, Y_{0i} \perp D \,|\, X)$ (Wooldridge, 2002). The CIA requires that the set of explanatory variables (X) should contain all the variables that jointly influence the outcome with no treatment as well as the selection into treatment. The second assumption is the common support or overlap condition $(0 < P(T) < 1)$ ensures that treatment observations have comparison observations “nearby” in the propensity score distribution (Heckman et al., 1997). This implies that PSM depends on a roughly equal number of users and user observations so that region of common support can be found and user units would therefore have to be similar to non-user units in terms of observed characteristics which are unaffected (Khandker et al., 2010).

The propensity weighting method uses the propensity score and estimates both average treatments effects (ATE) and treatment effect on the treated (ATT) consistently (Wooldridge, 2002). The treatment effects are simply the differences in outcomes of treated and control groups.

4. Results and Discussions

4.1. Empirical Results

The estimation of the binary probit explained the behavior of biogas technology adoption decisions. The choice of explanatory variables is based on previous literature suggestions that a wide range of socio-economic, technical, and physical factors influence new technology adoption in developing countries (Feder et al., 1985; Foster and Rosenzweig, 2010; Hadush et al., 2019; Hadush & Gebregziabher, 2022; Cole et al., 2010; Conley & Udry, 2010; Duflo et al., 2011; Liu & Huang, 2013; Duquette et al., 2013). Marginal effects (ME) computed for the use decision are presented in Table 2. A set of explanatory variables was used for this estimation, revealing how these variables vary in terms of direction, magnitude, and significance in influencing adoption decisions.

The results from the probit model explaining the adoption of SF practice correctly predicted 80% of the responses (Table 2). The χ^2 for the log-likelihood test of the hypothesis that the regressors have zero influence on farmers' adoption was significant. Thus, the hypothesis that the variables have no explanatory power was rejected. The results of the Likelihood Ratio test and the Wald test showed that the inclusion of selected variables increased the model fit significantly. This was consistent with the hypothesis that there exists a strong relationship between these variables and the biogas adoption decision.

Econometric findings from Table 2 confirmed that 11 explanatory variables selected from the adoption literature shaped the decision to adopt biogas technology. The results show that patience induces biogas adoption. It has been argued that a high level of impatience prevents farmers from making long-term investments. This increases the likelihood that the individual will remain below the poverty line since poor people have forgone higher and more sustainable returns (Duflo et al., 2011; Le Cotty et al., 2014; Ashraf, 2009). Our result showed a positive association between biogas adoption and patience, implying that patient farmers have a 28% higher probability of biogas adoption than their impatient counter-participants. This concurs with our prior expectations and earlier findings (Yesuf, 2004; Le Cotty et al., 2014; Duflo et al., 2011; Hadush & Gebregziabher, 2022), whose findings stated that present-biased or impatient farmers postpone new technology adoption in Africa and Asia. Likewise, a study by Tarozzi and Mahajan (2011) using the time preferences of Indian farmers revealed that low adoption of re-treating bed nets is related to present bias. A recent finding by Liebenehm and Waibel (2018) indicated that individual farmers with high discount rates were found to have low prophylaxis take-up in West Africa.

Earlier findings indicate that risk preference affects farmers' willingness to try new practices (Greiner et al., 2009). It affects the adoption of new technologies in many ways and has been found to reduce the adoption of new technologies and practices since it demonstrates a fear of variance in outcomes (Brick and Visser, 2015; Di Falco, 2014). The variable representing risk preference is negative and significantly different from zero, suggesting that more risk-averse farmers are 7.05% less likely to adopt biogas technology, consistent with the findings of (Liu and Huang, 2013; Hadush & Gebregziabher, 2022; Liebenehm and Waibel, 2018), who revealed a negative relationship between risk aversion and technology adoption. Similarly, loss aversion is considered to affect technology adoption (Liu and Huang, 2013; Kijima, 2019). In this case, it is found that higher loss aversion, holding other variables constant, reduces the probability of biogas adoption by 12.6%. The finding concurs with the findings of (Liu and Huang, 2013; Liebenehm and Waibel 2018; Kijima, 2019; Hadush & Gebregziabher, 2022) whose results show a negative relationship between loss aversion and technology adoption.

Table 2: Probit Estimation Result

adoption factor variables	Robust Marginal effect	Std. Err.	z	P>|z|	X_i-mean
Sex (Female=1)	0.0007	.22141	0.00	0.998	0.195
Age(year)	-0.0172	.00608	-2.82	0.005***	47.35
Planed Tree(number)	0.0001	.00032	0.03	0.974	221.3
Marital status (Married=1)	0.3044	.12693	2.40	0.016**	0.65
Farm size(hectare)	0.2616	.27481	0.95	0.341	0.437
Family size(unit)	0.1391	.04625	3.01	0.003***	5.26
Cattle holding(unit)	0.0558	.02039	2.74	0.006***	4.365
Electric connection(Grid=1)	-0.3408	.10622	-3.21	0.001***	0.175
Market distance(minutes)	-0.0113	.00483	-2.34	0.019**	41.85
Technical assistance (Yes=1)	0.2520	.10855	2.32	0.020**	0.535
Farm Income (ETB)	7.59e-06	.00001	1.07	0.283	12421
Water Source(available=)	0.4934	.10854	4.55	0.000***	0.425
Patient (Early choice in both)	0.2833	.16339	1.73	0.083*	0.15
Risk aversion (safe choice)	-0.0706	.03775	-1.87	0.062*	4.205
Loss aversion (safe choice)	-0.1265	.05766	-2.19	0.028**	5.545
Summary statistics					
Number of observation	200				
Wald chi2(15)	76.23				
Prob>chi2	0.0000				
Pseudo R2	0.6367				
Log likelihood	-49.83454				
Goodness of fit Hosmer-Lemeshow's chi-squared (γ) = 6.72	Prob > chi2 = 0.5667				
Goodness of fit Pearson chi-squared (χ2) = 155.39	Prob >chi2 = 0.9384				

NB: ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Figures in parentheses are standard errors

The variables farm size, farm income, and planted trees had expected signs with a positive effect on biogas adoption in line with those of (Mengistu et al., 2016; Smith et al., 2015; Omer, 2012) but were found to be statistically irrelevant. As the age of household heads increases by one year, the adoption of biogas decreases by 1.7%. This reflects that younger household heads were found to be more likely to adopt biogas technology than older households because older people are more risk-averse than younger people, concurring with the findings of (Kabir et al., 2013; Walekhwa et al., 2009) who reported a negative relationship between age and biogas adoption. As expected, the variable family size appears to be a positive factor, causing biogas adoption to increase by about 13.9%. Similar findings are reported by Wang et al. (2011), who found that more labor positively influenced households' willingness to adopt biogas. The value of the marginal effect for cattle size indicates that the probability of adopting biogas technology increases by 5.6% compared to their counterparts in the study area. This finding is consistent with the earlier study by Iqbal et al. (2013), who posit that an increase in the number of cattle increased the probability of biogas adoption.

Empirical results show that households with access to grid electricity were less likely to adopt biogas technology than their counterparts, increasing biogas adoption by 34%. Contrary signs are found in the works of Berhe et al. (2017), who found that farmers with electric access have positive energy preferences towards the use of firewood and dried dung. Married household heads were found to adopt biogas technology more than single household heads in the study. The marginal effect of marriage indicates that the probability of adopting biogas technology for married households was found to be about 30.4% higher in the study area. This is in conformity with that of Mwirigi et al. (2014) in Kenya and Mengistu et al. (2016) in Ethiopia, who confirmed that married households were more likely to adopt biogas technology compared to single households. Results further showed that the variable sex has a positive sign but is statistically insignificant. This reflects that female-headed farmers are more likely to allocate more attention and time to biogas investment than male-headed farmers, in line with that of Wang et al. (2013).

Distance from the market may affect biogas adoption by increasing or decreasing the cost of transporting construction materials. As anticipated, each additional distance is associated with an estimated 1.1% decrease in the use of biogas technology. This finding agrees with that of Kelebe et al. (2017), who revealed a significant negative relationship between biogas adoption and market distance. For households that get technical assistance, the probability of adopting biogas was 25% higher than the probability for households without technical assistance. Similar results are found in the works of Hazra et al. (2014) and Momanyi and Benards (2016), who noted that a lack of skilled labor and technical knowledge had hindered biogas dissemination and adoption in Ghana. The marginal effect of water source indicates that those who have sufficient water availability were found to be 49% more likely to adopt biogas technology than those who do not have sufficient water availability in the study area. This finding is in consonance with the idea that the limited availability of water was a constraint to biogas operation and production (Mwirigi et al., 2014).

4.2 Impact of Biogas Adoption.

Biogas is both a clean and environmentally friendly biotechnology with considerable positive environmental externalities. It is also a clear-burning fuel free of indoor pollution. It mitigates family health hazards from indoor air pollution and exposure to smoke from conventional burning. A study conducted by Ghimire (2015) concluded that biogas technology has an economic dividend in that it saves expenditures on fuel sources, saves time to utilize in other income generation activities, increases soil fertility and reduces the required quantity of chemical fertilizer, reduces health expenditures due to a decrease in smoke-borne diseases, and creates employment opportunities. It burns cleanly, so its use minimizes eye illnesses that result from the burning of traditional biomass fuels. Biogas technology provides health benefits not only to its users but also to the whole community (Aggarangsi et al., 2013). Moreover, biogas is a clean cooking fuel, increasing time for washing cooking utensils by an average of 39 minutes per day and saving time for attending school or other productive purposes (Arthur et al., 2011).

Table 3: Impact Estimation Results

	A. Health Expenditure in ETB/year (1USD≈30ETB in2019)				
Types of matching	n.treated	n.control	ATT	BSE	t-value
Nearest Neighbor (NN) Matching	88	27	-169.318	79.026	-2.143**
Caliper/Radius Matching	88	84	-216.360	43.961	-4.922***
Kernel Matching	88	84	-249.850	69.575	-3.591***
Stratification & Interval Matching	88	84	-254.124	72.985	-3.482***
	B. Biomass consumption Kg/year				
Types of matching	n.treated	n.control	ATT	BSE	t-value
Nearest Neighbor (NN) Matching	88	27	-690.893	315.139	-2.192**
Caliper/Radius Matching	88	84	-635.188	195.818	-3.244***
Kernel Matching	88	84	-627.505	248.568	-2.524***
Stratification & Interval Matching	88	84	-637.009	190.658	-3.341***

NB: ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Bootstrapped standard errors with 100 replications

The estimated impacts of biogas adoption are presented in Table 4.4. The predicted outcomes from the PSM models using different matching algorithms are used to compute the average treatment effect on the treated (ATT). Referring to **Table 3a,** the result showed that the impact of biogas technology adoption on average annual medical expenses is negative and significant. The finding shows that the decrement in annual health expenditure for user households ranges from a minimum of 169.318 ETB using nearest neighbor (NN) matching to a maximum of 254 ETB in the case of stratification and interval matching. This coincides with the results of Abadi et al. (2017), whose results revealed a negative relationship between biogas use and medical expenditure. The results from **Table 3b** showed that the adoption of biogas technology significantly reduces households' total biomass consumption in kg per year. Adopters of biogas are seemingly better off than non-adopters in terms of biomass consumption (kg) per year, implying that the adoption of biogas decreases biomass consumption from a minimum of 627 ETB using Kernel Matching to a maximum of 690 ETB in the case of Nearest Neighbor (NN) Matching. This result agrees with the findings of (Sakarombe, 2017) in that biogas technology reduces emissions by reducing firewood consumption and, hence in conserving forests.

5. Conclusions and Suggestions

Enhancing rural farmers' livelihoods using environmentally friendly biotechnology has become an increasingly global challenge. Biogas technology is a clean-burning fuel free of indoor pollution that improves fuel or energy efficiency, saves time for schooling or other productive activities, and reduces environmental pollution and health problems. The study investigated the adoption of biogas technology using the probit model and its impact on households' health expenditure and biomass consumption by estimating the propensity score matching in Ethiopia.

The empirical results indicated that adopting biogas technologies has economic and environmental benefits. The technology is economical and environmentally sustainable as it reduces annual medical expenditure and biomass consumption in KG per day. It was found that risk and time preference parameters significantly determine the adoption decision of biogas technology. We found that farmers' aversion to risk and loss constrains the adoption of new biogas technology. Results suggest that the low take-up of biogas technology is related to loss aversion and impatience, implying long-term higher returns are forgone and increasing the risk of perpetual poverty. Distance to the nearest market and technical assistance barriers have been hindering biogas technology adoption. As expected, the availability of water, family size, and cattle size were shown to be essential for inducing biogas technology adoption. As a complement, biogas technology adoption responds positively to marriage and negatively to age.

Interventions that overcome the constraints related to technical assistance could facilitate the uptake of biogas technologies. We argue that technical assistance and the availability of water sources should be in place to enhance the uptake of biogas technology. Strategies to counteract risk aversion and high discounting behavior are important to improve the adoption of new technology, thereby enhancing the smallholder economy in Ethiopia.

Ethiopia, being one of the least developed countries in Sub-Saharan Africa, suffers from very low per capita energy consumption and the dominance of traditional biomass fuel use. In 2009, traditional biomass fuels accounted for 92% of the total energy consumption, whereas modern fuels constituted the remaining 8%. Therefore, this paper has three policy implications: First, promoting biogas technology adoption in the region is a paramount policy, not only to improve the economic livelihood of rural households but also to conserve the environment by reducing the firewood and charcoal destruction and extraction rates in the region. To this effect, East African countries, including Ethiopia, are required to move forward in promoting biogas technology regionally as well as internally within their regions. Second, more than 70% of the nation's population entirely depends on natural forests as firewood. Subsidizing bio-digesters in rural farm households in an effort to provide a substitute for firewood, charcoal, and dried animal dung materials not only improves health and sanitation but also saves time for fuel and charcoal collection. Third, policymakers should then consider the importance of farmers' risk and time preference when promoting new technology adoption.

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