ORIGINAL ARTICLE

Impact of Radio on Technical Efficiency of Farmers: The Case of Wheat Producing Farmers in Ethiopia

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ABSTRACT

This paper examines the effect of radio in improving technical efficiency focusing on wheat producing farmers selected from 61 woredas in Oromia, Amhara, SNNP and Tigray regional states in Ethiopia. Propensity score matching (PSM) approach was used as it is becoming increasingly a standard approach for evaluating impacts using observational data. The study indicated that technical efficiency level is significantly higher for farmers that have radio than those who have not. The use of radio appears to significantly increase the level of technical efficiency as wheat growing farm households who have radio are more efficient by 6% than those that don't have. The study concludes and recommends that using radio could be an effective strategy to improve agricultural efficiency in general and technical efficiency of farmers in particular which indicates the enormous potential of radio for the transformation of Ethiopia's agriculture.

Key words: Ethiopia, Impact, Radio, Technical Efficiency, Wheat

INTRODUCTION

Ethiopia is a predominantly agricultural economy as agricultural GDP constitutes 41% of total country's GDP (CSA, 2014/15). Agriculture is the major supplier of raw materials to food processing, beverage and textile industries (Endale 2011). It also accounts for 73 percent in terms of employment (UNDP, 2014) and contributes over 80% to the export sector (NBE, 2010/11). Moreover, food needs as well as the industrial demand for agricultural products increase due to population growth (Bor and Bayaner, 2009). All these needs, according to them, require an increase in the agricultural production. However, this has to be increased by improving the agricultural productivity per land area as most of accessible fertile lands have been cultivated (Matsumoto and Yamano, 2010). Asfaw et al. (2012) cited in Elias et al. (2013) asserted that achieving agricultural productivity growth will not be possible without developing and disseminating improved agricultural technologies that can increase productivity to smallholder agriculture.

Communication has been acknowledged for playing a prominent role in the success of adoption of innovations and agricultural production. In this regard, Admassie and Ayele (2004) as cited by Endale (2011) found that access to information is among the crucial variables affecting technology adoption in subsistence agriculture of the four major administrative regions of Ethiopia-Amhara, Oromia, Tigray and SNNP. The usefulness of research results is generally achieved through an efficient mechanism of information transfer (Oyegbami and Fabusoro, 2003). Several channels such as extension agents, individuals, farmers-to-farmers contact, print media and electronics media have been widely used to disseminate information to farmers (Olowu & Oyedokun, 2000). Mass media is an effective tool for creating awareness and mobilizing farmers to adopt and apply agricultural technologies and innovations. The success of agricultural development programs in developing countries largely depends on the nature and extent of use of mass media particularly radio in mobilizing farmers for the need for development (Ango, 2013). This is because radio can reach large

Audience at the same time and In terms of cost, it is an extremely economical medium as compared to other extension media and methods involving individual and group contacts. Radio is considered as a credible source of information and is taken as authentic, trustworthy and prestigious medium of communication" (Kakade, 2013).

Radio broadcasting was started in Ethiopia at the time of Emperor Haile Silassie in 1935. Up to 2005, there were only three radio stations namely; Ethiopia Radio, Radio Fana and the Voice of Wayane Tigray. It was after this time that regional states started to establish local radio stations. Up to 2012, there were 26 radio stations that were operational in the country. Various agricultural radio programs have been designed and transmitted by national, regional and FM radio stations across the country with particular emphasis on delivering various farm management, production techniques, disease and pest management as well as market related information that have direct influence in improving technical efficiency of farmers. The 2007 population and housing census indicated that there were over 5.6 million radio receivers in Ethiopia while there were a little more than 15.1 million households in the country. Thus, it was only about 37.5% of the households that had radio.

Despite the dearth of radio receivers in the country, there is a great discrepancy between urban and rural dwellers with regard to ownership of radio. Though 68.5% of urban households had radio, only 30.1% of the rural households had radio by that time with 84% of the population living in rural Ethiopia. However, more radio in rural areas were introduced as clearly indicated by the five rounds of the CSA Ethiopian welfare monitoring surveys undertaken between 1995 and 2011. Over the sixteen years gap between these years, the proportion of rural households owning radio has increased by 300.5% from 7.7% in 1995 to 30.8% in mid-2011 at country level. Considering only the latest seven years gap from mid-2004 to mid-2011 for which data is available, the national proportion of rural households in possession of radio has risen by 66.6% from its level of 18.5% in mid-2004. The findings of the two recent rounds welfare monitoring surveys of 2011 and 2004 also indicated the regional distribution of radio possession by rural households. As to these surveys, above country average proportion of radio possession among regions was observed in Benshangul-Gumuz (40.6%) followed by Afar (37.9%), Harari (37.4%) and Oromia (36.9%) in 2011. While radio ownership in the same year was around the country average in three of the regions (with Tigray 31.4%, Dire Dawa 30.9% and SNNP 29.8%), it was well below the country average in the rest regions (with Amhara 22.8%, Somali 23.8% and Gambela 26.2%). With regard to the percent change in proportion of rural households possessing radio between 2004 and 2011, only two Regions-Amhara (104.1%) and Benshangul-Gumuz (74.1%) showed an above country average overall growth rate. While two of the regions-SNNP (63%) and Oromia (59.1%) revealed a rate closer to the national average, most of the rest regions had a rate far below the national average (with Harari -13.4%, Somali 27.6%, Dire Dawa 38%, Tigray 44.5% and Afar 48.8%).

Negussie (2006) and Olowu et al (2000) indicated, the potential contribution of radio in transforming agriculture seems well understood and efforts to use radio in a way its potential could be reaped towards the development of agriculture seems very low. Improving the use of radio as main means of disseminating agricultural information for smallholder farmer should be guided by information specially in its impact it has created in improving farmers practices and overall efficiency. However, to the best of our knowledge information available in the area of impact of radio on technical efficiency is very scant specially in the context of Ethiopia. The hypothesis of this study is therefore, established on the premise that radio positively influences farmers' productivity through improving their technical efficiency. Previous studies in this area of research is very limited in Ethiopia. This study was, therefore, conducted with an objective of analyzing the impact of agricultural radio programs on improving the technical efficiency of wheat producing farmers in Ethiopia. This study will, therefore, contribute to the growing but scant literature in the areas of the role of ICT in general and radio in particular in transforming Ethiopia's agriculture by empirically examining the impact of radio on technical efficiency of wheat producing farmers in Ethiopia.

The rest of the paper is organized as follows. The second section explains the theoretical framework and empirical procedures used in analyzing impacts using observational data. The third section describes the data and presents some descriptive statistics of respondents using major variables used in the econometric model. The fourth section reports the econometric results and the final section presents conclusions and recommendations.

Theoretical framework & empirical procedure

Analytical framework for determining technical efficiency level: Cobb Douglas Stochastic frontier model

Koopmans (1951) provided a definition of technical efficiency as a producer is technically efficient if it is no longer possible to produce any further output without producing less of some other output or using more of some input.

Ferguson (1996) defined production function as a function that relates maximum possible output using a given amount of combination of inputs. The production technology of a farm is represented by a stochastic production function specified as:

$$Y_i = f(X_i; \beta)\exp(v_i - u_i) \quad (1)$$

Y_i denotes output for firm i, X is the vector of inputs used in the production process by i^{th} firm, β is a vector of parameters to be estimated, $f(X_i; \beta)$ is a true representation of a farm production function, u_i is non-negative random variable associated with technical inefficiency, assumed to be independently and identically distributed, $N(0, \sigma_u^2)$ and truncated at Zero, of the normal distribution with mean μ and variance $\sigma_u^2(|N(0, \sigma_u^2)|)$. v_i represent the stochastic error term.

The maximum likelihood estimates yieldβ, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and$\gamma = \sigma_u^2/\sigma^2$. Following Jondrow et al. (1982), the technical efficiency estimation is given by the mean of the conditional distribution of inefficiency term μi given ε; and thus defined by:

$$E\left(\frac{u_i}{\varepsilon_i}\right) = \sigma^2\left[\frac{f(\frac{\varepsilon_i\lambda}{\sigma})}{1 - F(\frac{\varepsilon_j\lambda}{\sigma})} - \frac{\varepsilon_i\lambda}{\sigma}\right] \quad (2)$$

Where f and F represent the standard normal density and cumulative distribution functions respectively, and:

$$\lambda = \frac{\sigma_u}{\sigma_v} \quad (3)$$

where ${\sigma_v}^2$ and ${\sigma_u}^2$ are variance of the stochastic model and the inefficiency model respectively. Equation (1) and (2) provides estimate of u and v after replacingε, σ and λ by their estimate.

Analytical framework for evaluation of radio impact on technical efficiency

Radio ownership is not random. There are several observable household and farm characteristics and institutional factors that affect radio ownership. This poses serious challenge on the estimation of the causal impact of radio which ultimately leads to selection bias. This may arise from households' self-selection into owning radio or from endogenous program placement. Households may decide, based on their access to productive resources, to buy and own radio and therefore self-select into the program. Therefore, the main challenge of a credible impact evaluation is the construction of the counterfactual outcome, that is, what would have happened to participants in absence of treatment (Heinrich et al., 2010). Since this counterfactual outcome is never observed, it has to be estimated using statistical and econometric methods. In order to address selection problem propensity score matching (PSM) is becoming an increasingly used approach.

PSM is being used in wide range of impact evaluation studies. Among these, Heckman, Ichimura and Todd (1998), Dehejia and Wahba (2002), and Smith & Todd (2005) used PSM techniques to estimate the impact of labor market and training programs on income; Jalan and

Ravallion (2003) evaluate antipoverty workfare programs; and Persson, Tabellini and Trebbi (2003) analyze the impact of electoral reform on corruption. This study also employs PSM to estimate the impact of radio on technical efficiency of wheat producing farmers in Ethiopia. PSM uses information from a pool of units that do not participate in the intervention to identify what would have happened to participating units in the absence of the intervention. The general idea of PSM involves pairing treatment and comparison units that are similar in terms of their observable characteristics. When the relevant differences between any two units are captured in the observable pretreatment covariates, which occurs when outcomes are independent of assignment to treatment conditional on pretreatment covariates, matching methods can yield an unbiased estimate of the treatment impact (Cochran and Rubin, 1973 and Rosenbaum, 1995).

In PSM, we assume that data can be obtained for a set of potential control units, which are not necessarily drawn from the same population as the treated units but for whom we observe the same set of pretreatment covariates, X_i. If for each unit we observe a vector of covariates X_i and $y_{i0} \perp T_i|X_i, \forall_i$, then the population treatment effect for the treated, $\tau|_{T=1}$, is equal to the treatment effect conditional on covariates and on assignment to treatment $\tau|_{T=1,X}$, averaged over the distribution $X|T_i = 1$ (Rubin, 1977).

One way to estimate this equation would be by matching units on their vector of covariates, X_i. Rosenbaum and Rubin (1983) suggest the use of the probability of receiving treatment conditional on covariates. Accordingly, the probability of receiving treatment conditional on covariates is expressed as: let $p(X_i)$ be the probability of a unit i having been assigned to a treatment defined as:

$$p(X_i) \equiv \Pr(T_i = 1|X_i) = E(T_i|X_i),$$

then

$$(Y_{i1}, Y_{i0}) \perp T_i|X_i \; f \; (Y_{i1}, Y_{i0}) \perp T_i|p(X_i)$$

Heckman, Ichimura, and Todd (1998) suggested the following to determine or compute the treatment effect:

$$\hat{\tau}|_{T=1} = \frac{1}{|N|}\sum_{i\epsilon N}\left(Y_i - \frac{1}{|J_i|}\sum_{j\epsilon J_i} Y_i\right)$$

where N is the treatment group, $|N|$ the number of units in the treatment group, J_i is the set of comparison units matched to treatment unit i and $|J_i|$ is the number of comparison units in J_i.

Selection of matching algorism

Matching between treatment and control groups is done using different options of algorithms (Rosenbaum & Rubin, 1983). The most commonly used matching algorithms includes; Nearest Neighbor Matching (NNM), radius matching and kernel matching. NNM is one of the most straightforward matching procedures in which individual from the comparison group is chosen as a match for a treated individual in terms of the closest propensity score. Variants of nearest neighbor matching include “with replacement” and “without replacement,” where, in the former case, an untreated individual can be used more than once as a match and, in the latter case, it is considered only once.

For a kernel matching method associate to the outcome y_i of treated unit i a matched outcome given by a kernel-weighted average of the outcome of all non-treated units, where the weight given to non-treated unit j is in proportion to the closeness between i

$$\hat{y}_i = \frac{\sum_{k\in\{D=0\}} K\left(\frac{p_i - p_j}{h}\right) y_j}{\sum_{k\in\{D=0\}} K\left(\frac{p_i - p_j}{h}\right)}$$

and j:

Control $j's$ outcome is y_j and is weighted by:

$$w_{ij} = \frac{K\left(\frac{p_i - p_j}{h}\right)}{\sum_{k\in\{D=0\}} K\left(\frac{p_i - p_j}{h}\right)},$$

Where h represents bandwidth to be selected.

In implementing the NNM, treated unit i is matched to that of non-treated unit j such that:

$$|p_i - p_j| = \min_{k\in\{D=0\}}\{|p_i - p_j|\}$$

For the caliper matching, for a predefined $\delta > 0$, treated unit i is matched to that of non-treated unit j such that:

$$\delta > |p_i - p_j| = \min_{k\in\{D=0\}}\{|p_i - p_j|\}$$

If none of the non-treated units is within δ from treated unit i, i is left unmatched. Hence, in this study all of the three widely used algorithms-kernel, NNM and radius/caliper matching algorithm were employed to check the robustness of estimated impact of radio on technical efficiency.

Data

The data used for this study is obtained from farm household survey conducted during 2015/16 by Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Center (CIMMYT). The data was collected with a purpose of wheat technology adoption analysis and its impacts on smallholder producers. The sampling frame covered seven major wheat growing agro-ecological zones that account for over 85% of the national wheat area and production distributed in four major administrative regions of Ethiopia. A total of 2017 farm households residing in the seven agro-ecological zones, in 26 administrative zones (provinces), 61 districts and 122 "kebeles"/villages/local councils were interviewed.

A multi-stage stratified sampling procedure was employed to select villages from each agro-ecology, and households from each "kebele"/village. First, agro-ecological zones that account for at least 3% of the national wheat area each were selected from all the major wheat growing administrative regions of Ethiopia: Amhara, Oromia, Tigray, and Southern Nations Nationalities and Peoples (SNNP). Second, based on proportionate random sampling, up to 21 villages in each agro-ecology, and 15–18 farm households in each village were randomly selected. The data was collected using a pre-tested interview Schedule by trained and experienced enumerators who have good knowledge of the farming systems and speak the local language.

RESULTS AND DISCUSSIONS

Descriptive statistics

Descriptive statistics for variables used in Cobb-Douglas stochastic model

Descriptive statistics of the five major inputs farmers used in the production of wheat and the output variable (wheat yield) is summarized on table 1. The natural logarithm of estimated mean value of each of these inputs and output were taken and included in the model.

Descriptive statistics for variables used in probit model-PSM

Different variables that were included in the probit model which describe the characteristics of the sample respondents are presented on table 2. Radio ownership status widely varies across regions. The proportion of households that have owned radio is 38% in Tigray, 45% in SNNP, 29% in Amhara and 54% in Oromia. The total average proportion of households that owned radio is 41.5%.

Age, education level and gender are the most important demographic factors that affect radio ownership as the descriptive statistics of these variables indicated significant difference between households that have radio and those that don't have. The average age of a household head for households that have owned radio is 44.4 years where as that for households that haven't owned radio is 47 years. This figure tentatively indicates that as age of the household head increases, the probability of owning radio could decrease. Households that have owned radio have larger family size. The average family size of households that have owned radio and those that haven't is 6.92 and 6.29 respectively. Farm household heads that can read and write tend to tentatively have higher probability of owning radio than those who can't. The descriptive statistics of the gender variable also tentatively indicated higher probability of owning radio when the household head is male.

As landholding size and total livestock unit (TLU) are key wealth status indicators of rural farm households, they are also directly related to radio ownership status. The descriptive statistics of these important wealth related variables indicates the existence of significant difference between households that have owned radio and those that haven't. The average land holding sizes for households that owned radio and for households that haven't are 1.80 ha and 1.32 ha respectively. The average TLU for households who have radio and that for those who haven't is 6.83 and 4.28 respectively. Farmers that are recognized as model farmers have more tendency to own radio than those farmers that are not. Credit has no influence in radio ownership status.

Table 1: Summary of descriptive statistics of variables used in Cobb-Douglas stochastic model

Variables	Description of Variables	Aggregate Mean(SD)
Output &Inputs		
OUTPUT	Wheat yield of a household (kg/ha)	21.48(2112)
LAND	Size of wheat farm cultivated by a household (ha)	0.70(0.72)
LABOR	Man-days[1] per hectare	0.29(37.5)
SEED	Quantity of seed used (Kg/ha)	120.4(164.7)
FERTILIZER	Quantity of fertilizer(DAP) used (kg/ha)	57.66(70.5)
	Quantity of fertilizer(UREA) used (kg/ha)	24.77(36.4)
OXENDAYS	Oxen-days used	16.46(16.5)

[1] Man-day is calculated based on regular and common working hours in the study areas which is equivalent to 8 hours.

Table 2: Descriptive statistics of key variables included in the *probit* model-PSM

Variables	Unit	Radio Ownership Status			
		Owners Mean(SD)	Non-Owners Mean(SD)	Aggregate Mean(SD)	X^2/t-stat.
Outcome variable					
Technical efficiency	%	0.71(0.13)	0.63(0.16)	0.66(0.15)	(14.1)***
Variables that affect radio ownership					
HHAGE	Years	44.4(11.45)	47.17(13.4)	45.93(12.6)	(8.34)***
FAMILYSIZE	#	6.92(2.36)	6.29(2.05)	6.57(2.21)	(8.11)***
LANDHOLDING	Ha	1.80(1.56)	1.32(0.98)	1.54(1.29)	(-1.64)***
TLU	TLU	6.83(4.85)	4.28(3.62)	5.43(4.40)	(-11.23)***
HHEDU (Read & write=1)	1=Yes	0.76(0.39)	0.51(0.49)	0.62(0.48)	(15.37)***
MOBILETELEPHONE	1=Yes	0.69(0.46)	0.32(0.46)	0.48(0.499)	(-2.14)***
HHgender (Male=1)	1=Yes	0.94(0.26)	0.89(0.29)	0.919(0.28)	(-1.28)***
MODELFARMER	1=Yes	0.53(0.49)	0.33(0.47)	0.42(0.49)	(-6.8)***
CREDIT	1=yes	0.06(0.25)	0.06(0.25)	0.06(0.25)	(0.96)

***, **, * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.
Source: Own computation, 2015/16.

Technical efficiency estimate

In measuring the impact of radio on technical efficiency, we first estimated technical efficiency level using a stochastic frontier approach. Estimates of the model parameters were computed using the frontier model with a Cobb-Douglas functional form. The real investigations for the occurrence of inefficiency were calculated by estimating the stochastic frontier production function and conducting a likelihood-ratio test. This test statistic is computed using *STATA software version 13*.

The likelihood ratio test for the null hypothesis $H_o: \gamma = 0$ is rejected due to existence of significant variation among wheat producers attributable to technical inefficiency. The lamda (λ) value is also greater than one which confirms the presence of inefficiency.

A series of preliminary likelihood ratio tests revealed that Cobb Douglas stochastic frontier model best fit the data given the more flexible translog frontier model, and the distribution of inefficiency best represented by the half-normal distribution. Table 3 shows estimated coefficients of land, labor, seed, fertilizer and oxen for stochastic frontier model of Cobb-Douglas production function. The coefficients associated with the inputs measure the elasticity of output with respect to inputs. Positive and significant values indicate that there is a potential for increasing output of wheat by increasing the level of inputs used in the production process.

The average technical efficiency level for the whole sample and for the four regions where the data is collected from is presented on table 4. The calculated mean technical efficiency is 0.66 and this technical efficiency level estimate is used as outcome variable in the impact evaluation model (PSM).

Table 3: Maximum Likelihoods estimate for wheat production frontier function

Variables	Coefficient	t-value
Constant	4.92***	(27.76)
lnLAND	0.43***	(10.69)
lnLABOR	-0.03	(-1.70)
lnOXENDAY	0.069*	(2.29)
lnSEED	0.361***	(12.41)
lnFERTILIZER	0.188***	(8.20)
δ^2_v	-1.813***	-19.78
Function Coefficient	1.01	
λ	1.73	
Constant	-0.120(-0.28)	
Log likelihood	-1165.1	
N	1465	

***, **, * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 4: Technical efficiency level estimate

Efficiency estimate	Proportion of Sample HHs disaggregated by regions (%)				
	Tigray	SNNP	Amhara	Oromia	Aggregate
Mean efficiency	0.70	0.61	0.61	0.69	0.66
Maximum	0.92	0.88	0.15	0 .94	0.92
Minimum	0.19	0.07	0.094	0.12	0.05
St.dev	0.13	0.15	0.17	0.13	0.14

Estimating propensity scores using probit model

The descriptive statistics of the major variables that affect radio ownership and the existence of differences in technical efficiency level between households that own radio and those who don't have indicate tentative impact of radio in improving technical efficiency. However, given that radio ownership is endogenous, a simple comparison of the technical efficiency has no causal interpretation. That is, the differences may not be the result of radio, but instead might be due to other factors such as differences in observed characteristics. Therefore, we need to employ robust impact evaluation techniques such as PSM to control for observed characteristics and determine the real impact of radio on technical efficiency of wheat producing farmers in Ethiopia.

A probit model was employed to estimate propensity score for radio owners and non-owners which is necessary for making comparison between the two groups. The probability of owning radio was estimated using demographic, economic and institutional variables such as age, education, family size, land holding size, model farmer, gender, TLU, mobile and credit.

The test for 'balancing condition' across the radio owner and non-owner groups was done and the result as indicated on figure 1 proved that the balancing condition is satisfied. Standardized bias and t-test for differences were used to check matching quality and if the covariates X are randomly distributed across radio owners and non-owner groups, the value of the associated Pseudo R^2 should be fairly low and likelihood ratio should also be insignificant (Rosenbaum and Rubin, 1985).

\Econometric estimate using probit model indicated that age and education have significant influence on ownership status of radio. This implies, young and educated household heads have higher probability of owing radio than old and uneducated household heads. This might be due to information seeking behavior of young people who tend to look for new information from different sources and hence younger and educated people use radio as one of the means for accessing various information. Similar to the finding of this study, Jensen, (2007); indicated that education positively and significantly affects accessing information through ownership of electronic media (radio and mobile). Contrary to this, the findings of Alia et al (2013) indicated insignificant influence of age and education level of household head. TLU and land holding size which are the most important wealth status indicators have positively and significantly affected probability of owning radio. Better-off farmers who have higher TLU and larger agricultural land are more likely to afford to buy radio. This finding is in line with the findings of Getaw and Godfrey (2015) which indicated larger proxy household wealth indicators such as TLU and landholding size positively influenced likelihood of owning electronic media like mobile telephone, television and radio. Being a model farmer is significantly influenced radio ownership at 1% level.

This might be due to the wider social network of model farmers and their higher tendency to search for various types of information from different sources. Credit has no role in influencing radio ownership as a result of which it was excluded from the estimation of propensity score. Only variables that have significant influence are used in estimating propensity score.

Table 5: Econometric estimates of variables that affect radio ownership

Variables	Coefficient	t-stat
Gender	0.226	(1.74)
HHAGE	-0.0595*	(-2.07)
HHEDU	0.298***	(3.80)
FAMILYSIZE	0.11*	(2.51)
LANDHOLDING	0.0272	(0.51)
TLU	0.0578***	(6.35)
MOBILETELEPHONE	0.705***	(9.69)
CREDIT	0.0917	(0.07)
MODELFARMER	0.266***	(3.75)
N	1609	

***, **, * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

The propensity scores for each observation is calculated using probit model to predict the conditional probability of radio ownership. The propensity score for radio owners range between 0.111393 and 0.9679 while for non-owners it range between 0.077901 and 0.9250, therefore, the region of common support for the distribution of estimated propensity scores of radio owners and non-owners ranges between 0.0779 and 0.9250. Observations whose propensity score lies outside this range were discarded. The visual presentation of the distributions of the propensity scores is plotted in Figure 1. The density distributions of the estimated propensity scores for the two groups indicates that the common support condition is satisfied as there is substantial overlap in the distribution of the propensity scores of both radio owner and non-owner groups.

The covariate balancing tests before and after matching is presented on table 6. The bias substantially reduced, in the range of 21-41% through matching. The *p-values* of the likelihood ratio tests indicate that the joint significance of covariates was always rejected after matching. The $pseudo\ R^2$ also dropped significantly after matching. The low $pseudo\ R^2$, low mean standardized bias, and the insignificant *p-values* of the likelihood ratio test after matching suggest that the proposed specification of the propensity score is fairly successful in terms of balancing the distribution of covariates between the two groups.

The different impact estimators were used to check for robustness of estimated treatment effect. According to the result obtained, all the matching estimators revealed that radio ownership has a positive and statistically significant impact on technical efficiency. As indicated on table 7, the average impact of radio ownership on technical efficiency is estimated by nearest neighbor matching (NNM), Kernel Matching (KM) and Radius (caliper) Matching (RM) methods. The table reports results based on the single NNM without replacement and the kernel estimator with 0.25 and 0.50 bandwidth.

The finding reveals that radio ownership has a significant impact on technical efficiency and that it increases average technical efficiency in the range of 6-7 % (Table 7).

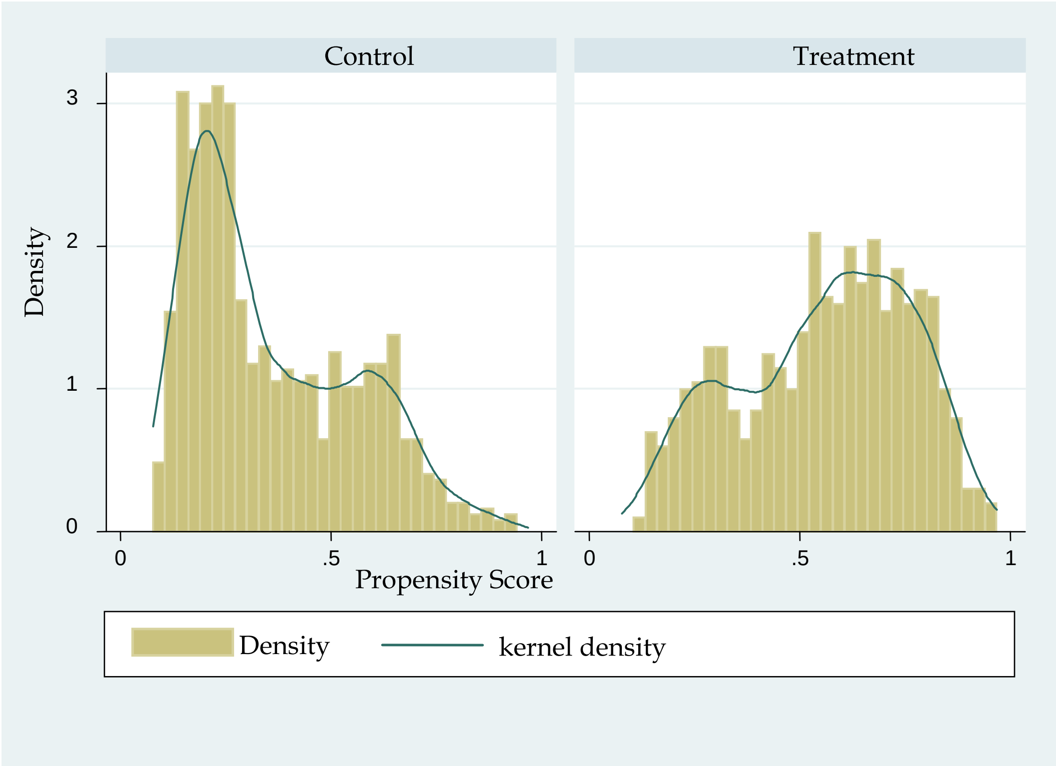

Figure 1: Distribution of propensity scores of radio owners and non-owners

Table 6: Propensity Score Matching Quality Test

Matching Algorithm	Before Matching			After Matching			Total Bias Reduction (%)
	Pseudo R^2	LR X^2 (p-value)	Mean Standardized Bias	Pseudo R^2	LR X^2 (p-value)	Mean Standardized Bias	
NNM1	0.14	291.95 (p=000)	45	0.001	2.15 (p=0.951)	35	22
KM2	0.14	291.95 (p=000)	45	0.01	23.53 (p=0.10)	35	22
KM3	0.15	291.94 (p=000)	44	0.05	98.3 (p=0.12)	34	21
Caliper matching (0.25)	0.15	291.95 (p=0.000)	9.0	0.024	36.59 (p=0.11)	5.2	41
Caliper matching (0.50)	0.15	327.53 (p=0.000)	6.9	0.063	105.72 (p=0.14)	4.8	30

NNM[1] =Nearest Neighbor Matching without replacement, KM[2] = with band width 0.25 and common support. KM[3] = with band width 0.50 and common support.

Table 7: Average Treatment Effects

Outcome Variable	Matching Algorithm	Mean of Outcome Variables Based on Matched Observations		
		Radio Owners	Non-Radio Owners	ATT
Technical efficiency	NNM[1]	0.73	0.67	0.06(0.007) ***
	KM[2]	0.73	0.67	0.06(0.007) ***
	KM[3]	0.74	0.67	0.07(0.007) ***
	Caliper matching (0.25)	0.74	0.67	0.07(0.009)***
	Caliper matching (0.50)	0.74	0.68	0.07(0.008) ***

Significance levels (*, **, *** denoting significance level at 10%, 5% and 1% respectively) are based on bootstrapped standard errors with 100 replications.
NNM[1] =Nearest Neighbor Matching without replacement
KM[2] = with band width 0.25 and common support.
KM[3] = with band width 0.50 and common support.

CONCLUSIONS AND RECOMMENDATIONS

The study was conducted with an objective of measuring the impact of radio ownership in improving technical efficiency of wheat producing farmers in Ethiopia. The study employed propensity score matching technique which is a robust impact evaluation technique that control for observable differences between control and treatment group so that the possible bias in estimating the actual impact could be reduced. In order to ensure robustness of impact estimates, different matching algorithms were employed and compared. The matching algorithms employed include Nearest Neighbor Matching (NNM), caliper/radius matching and Kernel matching. The study concludes radio ownership is very low in Ethiopia in which only 41.5% of rural farm households have radio. Despite this, radio ownership is making significant contribution for the development of Ethiopia's agriculture by improving technical efficiency of farmers. This indicate radio could provide an effective means and enormous potential for strengthening the country's agricultural extension programs that aims at increasing smallholder farmer’s production and productivity. By increasing availability of affordable radio to farming communities, it is possible to tap the potentials of radio to increase national agricultural production and productivity through enhancing farmer’s technical efficiency. As the number of households having radio continues to increase among farming communities and information services continue to adapt and proliferate, scope exists for a much greater rural productivity impact in the future.

This study; therefore, recommends use of radio to disseminating agricultural information to the different farming communities will contribute for effectiveness of the Ethiopian agricultural extension service delivery system. But use of radio for disseminating agricultural program should be accompanied by increasing availability of affordable radio for farmers.

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