Sveriges lantbruksuniversitet
Swedish University of Agricultural Sciences

Department of Economics

Off-Farm Income and Technical Efficiency of Smallholder Farmers in Ethiopia

- A Stochastic Frontier Analysis

Getahun Gemechu Abebe

Master's thesis · 30 hec · Advanced level
European Erasmus Mundus Master Program: Agricultural Food and Environmental Policy Analysis (AFEPA)
Degree thesis No 862 · ISSN 1401-4084
Uppsala 2014

Off-farm Income and Technical Efficiency of Smallholder Farmers in Ethiopia
- A Stochastic Frontier Analysis

Getahun Gemechu Abebe

Supervisor: Sebastian Hess
Swedish University of Agricultural Sciences (SLU)
Department of Economics

Assistant Supervisor Thomas Heckelei
University of Bonn
Institute of Food and Resource Economics

Examiner: Ing-Marie Gren
Swedish University of Agricultural Sciences (SLU)
Department of Economics

Credits: 30 hec
Level: A2E
Course title: Independent Project/ Degree Project in Economics E
Course code: EX 0537
Programme/Education: European Erasmus Mundus Master Program: Agricultural Food and Environmental Policy Analysis (AFEPA)
Faculty: Faculty of Natural Resources and Agricultural Sciences

Place of publication: Uppsala
Year of publication: 2014
Name of Series: Degree project/SLU, Department of Economics
No: 862
ISSN 1401-4084
Online publication: http://stud.epsilon.slu.se

Key words: Cobb-Douglas, Maximum Likelihood Estimation, Off-farm income, Smallholder Farmers, Technical Efficiency

SLU
Sveriges lantbruksuniversitet
Swedish University of Agricultural Sciences

Department of Economics

Acknowledgements

First, I would like to thank the European Commission for granting me the prestigious Erasmus Mundus scholarship. Next, I would like to thank my supervisor Dr. Sebastian Hess for his constructive comments and suggestion in this study. I am also thankful to Professor Ing-Marie Gren for her comments and follow-ups during the seminar sessions. Furthermore, my gratitude also goes to Professor Thomas Heckelei for his motivation to be my thesis examinor at University of Bonn. I am also thankful to AFEPA program coordinators Professor Bruno Henry de Frahan, Henrich Brunke, Dr. Ralf Nolten and Kristina Jansson for their help on practical matters. My special gratitude also goes to Wondemagne Tafesse for his continuous advises and motivations in writing this thesis. Friends, Tesfaye B. Birmaji, Wagari Shore and Selam Assefa deserve much more thank for their valuable advises. Finally, I would like to thank AFEPAians and other friends I have met during my stay in Germany and Sweden.

Abstract

As in most developing countries, agricultural production in Ethiopia is dominated by subsistence-based smallholder farmers, whose production and incomes from the sector are constrained by socio-economic, institutional, resource and environmental factors. These factors generally attribute for lower productivity of the sector, which in turn forces farmers to participate in off-farm activities in order to diversify their sources of income. However, participation in off-farm activities has direct and indirect influence on agricultural production.

The purpose of this study is to examine the impact of off-farm income on technical efficiency and farm output of smallholders in Ethiopia. The study used data from the 2009 Ethiopian rural household survey conducted by International Food Policy Research Institute. A Stochastic frontier model is used to address the objectives of the research. Results confirm the appropriateness of the Cobb-Douglas form of the production function over the Translog and Stochastic Frontier Analysis over the Ordinary Least Squares.

An instrumental variable regression framework is used to address the endogeneity of off-farm income in determining technical efficiency and farm output of farmers. The estimation results show that size of farm land, household size, off-farm income, gender and education of the household head are the most significant variables determining the value of farm output.

The average technical efficiency of farmers is only 53 percent, implying the existence of wider scope for improvement of their efficiency. In addition, maximum likelihood estimation result indicates that household size, education of the head, soil conservation, extension services and off-farm income are major factors for differences in technical efficiency among farmers. Particularly, the effect of off-farm income on farm output and technical efficiency is positive showing the spillover effects of income from off-farm activities on farm productions. Hence, policy makers should focus on increasing opportunities and access of off-farm activities to enhance production, productivity and overall wellbeing of the rural societies.

Abbreviations

CD	Cobb-Douglas
DEA	Data Envelopment Analysis
EHRS	Ethiopian Rural Household Survey
ETB	Ethiopian Birr
GDP	Gross Domestic Product
Ha	Hectare
HH	Household
IFPRI	International Food Policy Research Institute
IV	Instrumental Variable
Kgs	Kilograms
LR	Log-likelihood Ratio
MLE	Maximum Likelihood Estimation
OLS	Ordinary Least Squares
TE	Technical Efficiency
TL	Translog
SFA	Stochastic Frontier Analysis
SNNPRS	Southern Nation's Nationalities and People's Regional State
2SLS	Two stage Least Squares

Table of Contents

List of Figures

List of Tables

1. Introduction

1.1. Background of the study

Agriculture is still an important pillar of our planet's economy. The sector plays important roles in the development process of any nation by supplying food items, industrial inputs, generating foreign exchange, creating employment opportunities, contributing to gross domestic product (GDP) and expanding markets for industrial outputs. According to World Bank (2007), agriculture is the major source of income and employment for about 70 percent of the world's rural poor societies and 32 percent in the growth of GDP in these countries.

The sector is also the mainstay of the Ethiopian economy, constituting 45.6 percent of the economy in GDP, 90 percent of foreign exchange, 85 percent of total employment opportunities and 70 percent of industrial raw materials. It is also the major supplier of food stuffs for the entire population and hence plays a crucial role in contributing to country's food security programs. Besides, it is this sector that is expected to play an important role in creating surplus capital for the economic development processes in the country (Deressa, 2007).

In spite of its great importance to the country's economy, agricultural productions are however, subsistence-based and dominated by smallholder farm households that operate on farms of less than one hectare (Gebre-Selassie, 2004). Smallholder farming represents for about 90 percent of agricultural outputs and 95 percent of land area under crop production. In general, about 98 percent of coffee, the country's leading cash crop and 94 percent of food crops are produced by smallholders, while only 2 percent of coffee and 6 percent of crop production are produced by private and state commercial farms. Even though the present government has given higher priority to the agricultural sector, its productivity is however at its lowest level because of different interrelated socio-economic and climatic problems such as inappropriate use of farm land, over grazing, over cultivation, population growth, tenure insecurity, weak extension services, inadequacy of infrastructure, low access to fertilizer and pesticides (Deressa, 2007). According Rahman (2007), smallholder productions are generally characterized by low access to improved technologies, financial services, modern inputs, agricultural markets and irrigations services that attributed to variability of earnings from the farming sector. As a result, farmers are forced to participate in off-farm activities to overcome these obstacles.

Several studies suggest that participation in off-farm activities are initiated by two conventional factors, namely pull and push factors. The "push" factors are mandatory factors that force farmers to participate in off-farm activities in order to manage income risk and in this case off-farm income is used as a coping mechanism. These factors include shortfalls of agricultural production resulting from temporary failures due to, unexpected drought or long term factors such as shortages of farm land, absence of crop insurance, failures in input and credit markets and others (Reardon *,et al.*, 1998). On the other hand, the "pull" factors are incentives that attract households to non-farming sectors when non-farm activities offer higher return than the farm activities (Barrett *,et al.*, 2001).

According to Reardon *,et al.* (1998), household's participation in off-farm activities may also differ depending on their level of wealth. Conventionally, poorer households have more averse types of negative shocks to their production and they have less capacity to cope up with these shocks. Thus, they are expected to diversify their income sources more than richer households.

Off-farm income constitutes for about 25 to 40 percent in the total income of households in Ethiopia.Woldehanna (2000) indicated that off-farm income constitutes for about 35 percent in the total income of households from his study northern part of Ethiopia. Similarly, Beyene (2008) reported that 57.3 percent of farm households are participants in off-farm activities. Latest studies such as Bedemo *,et al.* (2013) reported that about 73.5 percent of households participate in off-farm activities in their studies in three districts of the country; Guto Gida, Gida Ayana and Jima Arjo.

Unskilled wage works in others' farm, unskilled non-farm[1] works, skilled and professional works as teacher, clerical, government and health worker, trader, driver, weaver, tailor and paid developmental works (for instance, food-for-work) are major off-farm activities in the country (Woldehanna, 2002). In general, farm households participate in one or more types of these activities to diversify their sources of income.

Even though households' participation in off-farm activities have considerable effects on the productivity of the farming sector, the possible link is not clear (Yue & Sonoda, 2012). As documented in different studies, it can be positive or negative or nil depending on where income from off-farm activities are invested. If incomes generated from off-farm activities

[1] Non-farm income and Off-farm income are different in the way that non-farm excludes wages earned in the agricultural sector; whereas, off-farm income is broader and includes all incomes generated out of own farm.

are spent as investment in the farming sector in the form of purchase of modern inputs and adoption of new technology, then the sector's production will be enhanced. On the other hand, the absence of labor in the agricultural sector negatively affect the productivity of the sector if incomes generated in the off-farm activities are spent for consumption or used as a means to leave the agricultural sector (Feng, 2008; Pfeiffer *,et al.*, 2009; Babatunde, 2013).

Using panel data on Slovenian farms, Bojnec & Ferto (2011) for example studied the impact of off-farm income on farm's technical efficiency. Their finding indicates positive association between off-farm income and technical efficiency. Similarly, Yue & Sonoda (2012) also confirmed that farmers with off-farm wage are more efficient than those without off-farm wage in their studies on Chinese farmers. On the other hand, Kumbhakar *,et al.* (1989) found negative correlation between the level of technical efficiency and off-farm income from their studies on Utah dairy farm households and Chang & Wen (2011) confirmed differential impacts of off-farm income on technical efficiency of Taiwanese farm households.

In developing countries, like Ethiopia, where income from farm activities varies considerably, farm households usually participate in off-farm activities to supplement their agricultural income (Beyene, 2008). Hence, off-farm income is expected to enhance their production and productivity in farming. However, it is not known to what extent households with off-farm income are better off than those without off-farm income and whether there exists variability in the level of technical efficiency among the two groups of households in the study areas. Therefore, this study intends to analyze the effects of off-farm income on technical efficiency and aims to fill the gap in this area.

1.2. Objective of the study

The general objective of this study is to examine the potential effect of off-farm income on technical efficiency of farmers in Ethiopia. Specifically, the study intends to

- identify factors determining technical efficiency of farmers,
- estimate the effect of off-farm income on the value of farm output and
- identify factors determining off-farm income.

1.3. Research Questions

This study aims to answer the following research questions:

- What is the existing mean efficiency of households?
- What determines efficiency and productivity of smallholders' production?

- What is the link between off-farm incomes and the observed level of technical efficiency for households?

1.4. Scope of the study

This study mainly focuses on productivity of smallholder farmers in Ethiopia. It estimates their technical efficiency and assesses the impact of off-farm income on the level of efficiency. It uses the 2009 rural household survey data obtained from International Food Policy Research Institute (IFPRI) to achieve the objectives. The data however, cover crop production in major regions of the country more explicitly while details on livestock subsectors and peripheral regions are not covered.

1.5. Relevance of the study

In countries in which growth and prosperity of the agricultural sector determine the fate of the entire economy, increasing the sector's productivity plays a greater role in increasing economic growth. Understanding the possible link between on-farm and off-farm activities plays a vital role in enhancing productivity of the farming sector and gives relevant policy information for the betterment of off-farm sectors. Thus, results from this study will provide information for stakeholders in government and extension services on how to increase the productivity of the farming and non-farming sector. Besides, it adds to the existing literature in the area of efficiency and off-farm income.

1.6. Organization of the study

The rest of the thesis is structured as follows. Chapter two presents the theoretical approaches of the study. It mainly covers microeconomic theories of production and efficiency measures. Chapter three focuses on literature review. It covers a broader range of empirical literatures on determinants of efficiency and the linkage between off-farm income and technical efficiency. Chapter four discusses methodological framework of the study. It begins with the overall descriptions of the study areas followed by the specification of the empirical model, description of model variables and finally gives brief explanation of estimation techniques. Chapter five presents the descriptive and econometric results.The last chapter summarizes the empirical findings of the study and draws appropriate policy recommendations.

2. Theoretical Approach

2.1. Overview of production function and efficiency

Estimation of production functions and technical efficiency is one of the most popular areas of research. In microeconomic theory, production is defined as the process of transforming inputs (raw materials) into outputs. A production function represents technological relationships between inputs and outputs. In particular, it shows the maximum level of output the firm can produce combining the existing inputs (Besanko & Braeutigam, 2005). A particular production function can be specified as:

$$f(x_i) = \max\{y_i : T(x_i, y_i)\} \qquad (1)$$

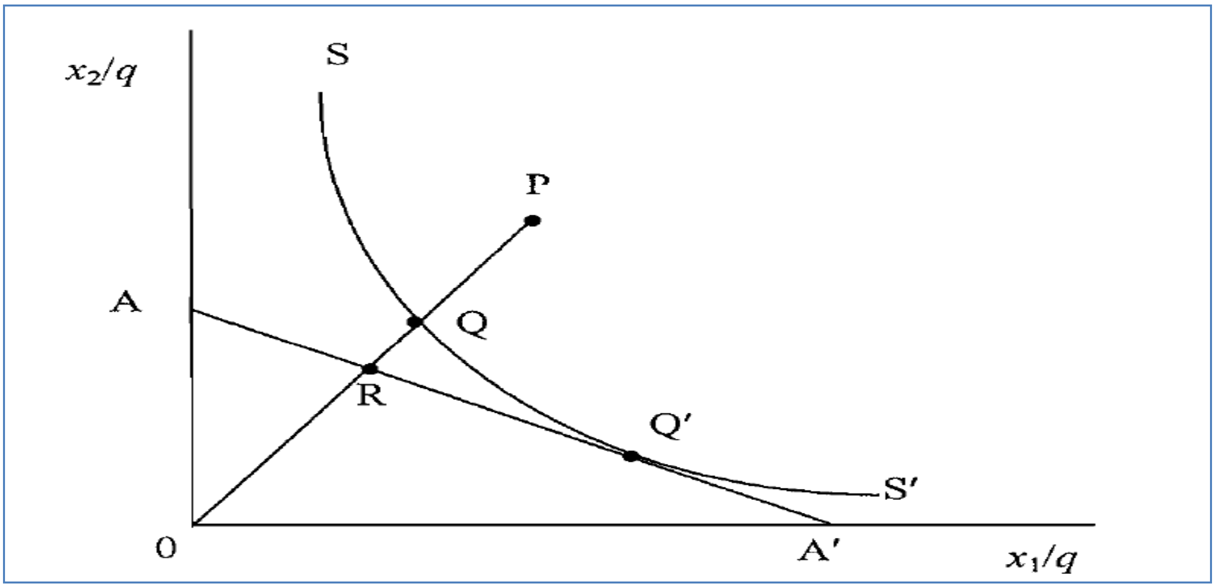
Where y_i the maximum level of output (frontier output) the firm can produce, x_i is the quantity of various inputs employed and $T(x_i, y_i)$ is the technological relationships between inputs and outputs. Given the existing level of inputs, three assumptions are usually made on frontier productions: (1) any production on the frontier output is attainable and efficient, (2) any production possibilities below the frontier level are attainable, but technically inefficient and (3) any production points above the frontier level are unattainable.

In general, the level of output can be increased in several ways. Firstly, by expanding the level of inputs used in production. This approach is called "horizontal expansion". However, increasing use of inputs is only possible if either the price of inputs decrease or the price of output increases. Secondly, output can be increased by enhancing efficiency in production. This approach is termed as "improvement approach" and requires the improvement of socio-economic, institutional and environmental constraints to enhance production using the existing inputs. Thirdly, output can be also increased by improving the technology in production. This includes use of improved techniques of production, improved seeds, modern fertilizer and chemicals. This approach is termed the "transformation approach" (Alene, 2003).

Most often, different studies use the terms *productivity* and *efficiency* interchangeably, though they are not exactly the same. Productivity refers to the ratio of output(s) to input(s) while; efficiency is the highest productivity level from each input level (Coelli & Rao, 1998). Farrell (1957) classified efficiency as technical (physical), allocative (price) and economic (overall) efficiency. Technical efficiency shows the ablity of farmers to produce maximum amount of output using the existing level of inputs. On the other hand, allocative efficiency measures the ability of farmers to use inputs in an optimal proprtion, given the price of inputs and outputs. A firm is economically (overall) efficient if it achieves both technical and allocative efficiencies.

For a given firm which uses two inputs (X_1 and X_2) to produce a single output (q) under a constant return to scale, Farrell (1957) illustrated the three types of efficiency using the following figure. The isoquant SS' represents the different combinations of the two inputs that the firm uses to produce a given amount of output and deviations from the isoquant implies technical inefficiency of the firm. thus, if the firm for example uses inputs at point P to produce a unique output on the isoquant; technical inefficiency of a firm is represnted by the segment QP, which shows the amount by which all inputs could be proportionally reduced without a reduction in the level of output. This can be expressed in percentage terms by the ratio of $QP/0P$ (Coelli ,*et al.*, 2005).

Figure 1: Graphical representation of Technical and allocative efficiencies



Thus, the technical efficiency of a firm is one minus the ratio of $QP/0P$ as shown in equation (2). On the other hand, allocative efficiency is measured by the ratio of input prices represented by the slope of isocost line AA', whereas economic (overall efficiency) is the product of technical and allocative efficiencies (Coelli ,*et al.*, 2005).

$$\text{Technical efficiency } TE = 0Q/0P = 1-(QP/0P) \quad (2)$$

$$\text{Allocative efficiency } AE = 0R/0Q \quad (3)$$

$$\text{Economic efficiency } EE = TE\ x\ AE = (0Q/0P)\ x(0R/0Q) = (0R/0P) \quad (4)$$

2.2. Measures of technical efficiency

In frontier models, technical efficiency is measured based on the performance of an individual producer compared to the most efficient producer in the industry. Various approaches have been used to measure efficiency of a producer. The most widely used approaches are *Stochastic Frontier Analysis (SFA)* and *Data Envelopment Analysis (DEA).* The DEA is a non-parametric approach that involves mathematical programming; whereas the SFA is a parametric approach that uses econometric methods. The DEA approach assumes that all deviations from the frontier output (for example, due to bad weather, strike and shortage of inputs) are due to technical inefficiency; whereas, SFA approach considers both an inefficiency component and a random error.

The SFA approach is usually preferred to estimate efficiencies of production systems. This is mainly because of two reasons: (1) the very nature of agricultural productions depends on climatic conditions and is affected by measurement errors that attribute for statistical noise in data sets and (2) stochastic frontier models allows decomposition of error terms between statistical noises and inefficiencies measure that enables statistical tests on the validity of model specification (Gelaw, 2004; Chen, 2007).

Battese & Coelli (1993) explains stochastic frontier production as follows:

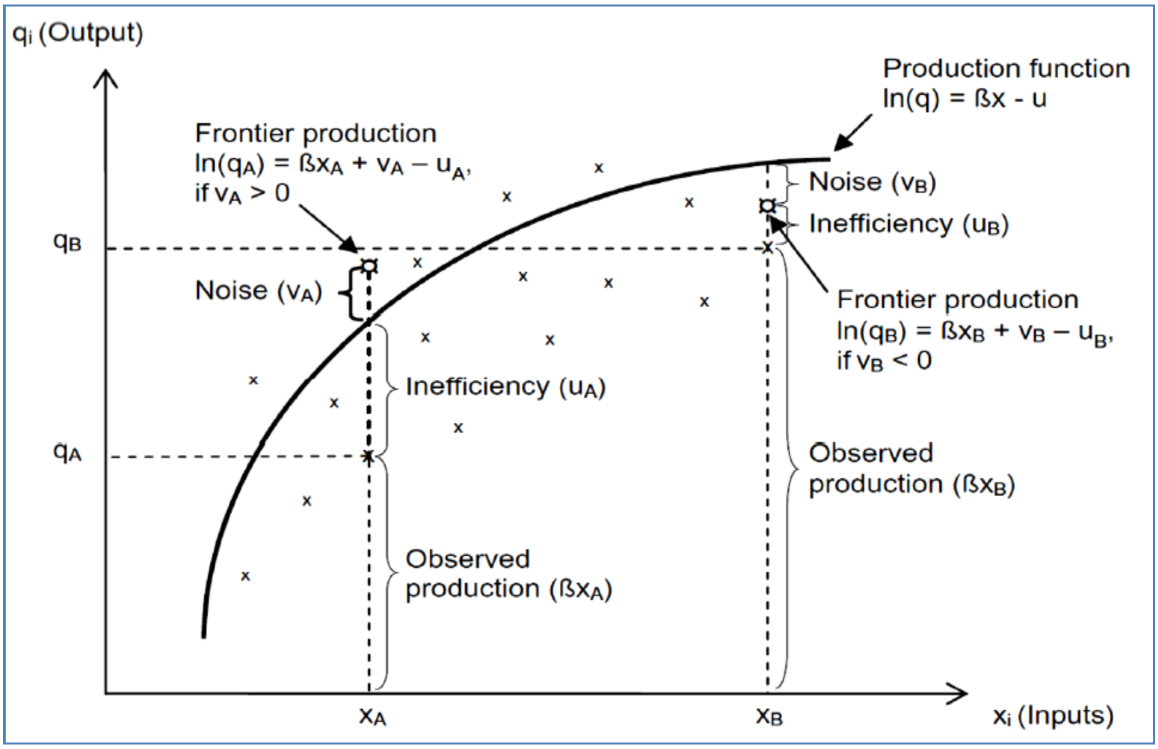
> "*The stochastic frontier production function postulates the existence of technical inefficiencies of production of firms involved in producing a particular output. For a given combination of input levels, it is assumed that the realized production of a firm is bounded above by the sum of a parametric function of known inputs, involving unknown parameters, and a random error, associated with measurement error of the level of production or other factors, such as the effects of weather, strikes, damaged product, etc. The greater the amount by which the realized production falls short of this stochastic frontier production, the greater the level of technical inefficiency".*

Given a Cobb-Douglas form of stochastic frontier production function expressed in equation (5),

$$\ln(q_i) = \beta_i X_i + v_i - u_i \qquad (5)$$

Where $\ln(q_i)$ is the logarthm of output of the ith farm household, β_i is a $(k\,x1)$ vector of unknown parameters to be estimated, X_i is a $(1x\ k)$ vector of inputs used in the production of the ith output, v_i is a random error measuring statistical noise and u_i is a non-negative error term measuing inefficiency effects, figure(2) shows the graphic illustration of the production function.

Figure 2: Graphical illustration of stochastic frontier production function



Source: (Neumann ,*et al.*, 2010)

Assuming two farm housholds, A and B, production inputs are shown in the horizonal axis and outputs are shown in the vertical axis. Farmer A and B use X_A and X_B level of inputs to produce q_A and q_B level of output. The points marked by × shows the observed values whereas, ¤ shows the frontier values. If there is no inefficiency effects in the production (i.e. $u_A = 0$ and $u_B = 0$) then the frontie level of outputs would be $\ln(q_A) = \beta_i X_A + v_A$ and $\ln(q_B) = \beta_i X_B + v_B$ for farmer A and B respectively. Further, the frontier level of output for farmer A lies above the determinstic level of output because of postive noise effects (i.e. $v_A > 0$) whereas that of farmer B lies below the determinstic level of output because of negative noise effects (i.e. $v_B < 0$)(Coelli ,et al., 2005).

3. Literature Review

3.1. Empirical studies on determinants of technincal efficiency

Most empirical studies on productivity and efficiency of farmers indicated that demographic, socio-economic, institutional, environmental and resource factors are the major determinants of efficiency differentials among farmers (Battese & Coelli, 1995; Bravo-Ureta & Pinheiro, 1997; Obwona, 2006; Nyagaka *,et al.*, 2010).

For instance, in their analysis on technical efficiency of smallholder farmers in Girawa district of Ethiopia, Ahmed *,et al.* (2013) confirmed that tehcnical efficiency of farmers is postively associated with education, extension services, livestock holdings and use of irrigation. Thus, education and extension services increases efficiency of a farmer by increasing awareness and ablity on the proper use of farm inputs, control of pest and crop disesases and overall mangement of farm productions. Livestock enhances efficiency directly through their use in farming operation; and indirectly by financing farm income in bad production years. Similarly, Asefa (2012) and Khai & Yabe (2011) also confirmed the importance of education, extension services and irrigation in improving technical efficency of farmers in their respective studies on Ethiopian smallholder farmers and Vetnamise rice producers.

Besides demographic and socio-economic factors, environmental conservation also plays key role in enhancing efficiency of farmers. For instance, in his study on the link between technical efficiency and environmental conservations in Ghana, Nkegbe (2012) found that those farmers adopting conservation practices are more technically efficient than non adopters. Similarly, Solis *,et al.* (2007) and Jara-Rojas *,et al.* (2012) also confirmed the role of soil, water and environmental conservations in enhancing technical efficiency of farmers.

The following table gives an overview of the findings of selected empirical studies on technical efficiency of farmers in Ethiopia. Most of these studies found that education and trainings of the household, extension services, farm size, off-farm income, access to credit and other socio-economic variables are the major determinants of technical efficiency of farmers.

Table 1: Summary of selected empirical studies on technical efficiency in Ethiopia

Author/s (Year)	Product	Sample size	Mean TE (%)	Determinants of Technical efficiency
Ahmed ,*et al.* (2013)	Crops	200	81.5	Education, extension services, farm land, livestock holdings, farmers training and participation in irrigation
Ahmed ,*et al.* (2014)	Maize	138	88	Family size, extension Services, access to credit and distance from the nearest market
Alene & Hassan (2003a)	Maize	60	76	Education, farm size, access to credit and timely delivery of modern inputs
Alene & Zeller (2005)	Crops	53	79	Improved technologies, education, extension and credit systems
Alemu ,*et al.* (2004)	Crops	254	75.68	Education, access to credit and proximity to markets
Fita ,*et al.* (2013)	Dairy	240	65	Education , exposure to media,Training and experience in dairy farming
Geta ,*et al.* (2013)	Maize	385	40	Farm size, number of oxen, agro-ecology and use of high yielding maize varieties
Haji (2007)	Vegetables, crops and livestock	150	91	Household asset, family size, farm size, off farm income and extension services
Kebede & Adenew (2011)*	Wheat	32	82	Distance from main road, managerial capacities and experience, Value of self-owned machineries
Tirkaso (2013)	Crops	562	40.2	Education, commercialization level of the farmer and access for communication devices such as cellphone and Radio

**Their study is on Commercial Farms*

3.2. Determinants of participation in off-farm activities

Income from off-farm activities plays a greater role in the livelihood of rural societies especially for subsistence-oriented households. Off-farm income directly contributes to households' income and indirectly influences agricultural productions with potential implications to policy makers (Kuiper *,et al.*, 2007). According to Woldehanna (2000), off-farm income can help farmers to purchease modern inputs, hire labour and reduce the varablity of farm income and smooth consumption.

Most studies in the area of off-farm business indicated that, demographic characteristic and financial and resource bases of the household are considered as main factors determining the decision of participation in off-farm activities. For example, using data on 200 households selected from 40 villages of Southeast Nigeria, Ibekwe *,et al.* (2010) examined factors determining non-farm income. Their findings shows that age of the household, education level, farm size and hours spent on farm activities are the most significant variables determining both farm and off-farm income. Specially, the size of farm land is positively associated with farm income whereas negatively correlated with off-farm income. This indicates that increases in the size of farm land increases farmers' willingness to operate in farm activities than participating in off-farm activities. This may further show the fact that small-sized farmers are driven out of farm businesses in the study areas. Besides, they also found positive association between household size and farm income and negative correlation between age of the household and off-farm income, implying less participation of older farmers in off-farm activities.

Bedemo *,et al.* (2013) studied factors determining the decsions to participate in off-farm work in western Ethiopia. The finding of their study shows that variables on household characteristics, access for credit and size of farm land are major determinats of decisions to participate in off-farm activities. They also noted the importance of off-farm income in reducing the problems of low agricultural productivity in the study area.

Zahonogo (2011) also examined factors determining participation non-farm activities in Burkina Faso and results of his study indicate that participation in non-farm activities mainly related to farm income, technologies in farm production, age and education of the household head, the number of working individuals in the household and the amount of rainfall. Accordingly, income from farm activities was found to have a negative effect on participation in the non-farm activities; whereas, other variables were found to have positive effects on participation in non-farm activities.

On his analysis on factors determining decisions to participate in off-farm activities in Ethiopia, Beyene (2008) estimated separate models for male and female members of a given farm households. His result indicates that training on off-farm activities and health status of the participant has considerable impact on their participation in off-farm activities. Besides the human capital variables, access to credit and income transfers were also found to have positive impact on off-farm activity participation. Accordingly, trained farmers are more likely to participate in off-farm business. In addition, transfer income and credit have a positive effect on participation in off-farm activities. He also confirmed that female members of households are less likely to participate in off-farm activities because of cultural factors and influences of the household head. His study however does not indicate the impact of off-farm activity participation on farm activities.

3.3. Empirical studies on agricultural production and off-farm income

Studies indicate that the impact of off-farm income on production and efficiency of farmer is not well understood yet. Even though most studies found positive relationships between the two variables, some authors also found negative or differential relations (Kumbhakar ,et al., 1989; Alene & Hassan, 2003b; Bojnec & Ferto, 2011; Chang & Wen, 2011). This section summarizes different empirical works on the link between off-farm income and farm output and technical efficiency.

From panel data on Slovenian farmers, Bojnec & Ferto (2011) examined the impact of off-farm income on technical efficiency. The finding of their study indicated a positive relationship between off-farm income and technical efficiency. Their result also revealed that off-farm income increases efficiency of framers over time, showing spillover effects of income from off-farm activities on farm activities. Furthermore, they also investigated the relationship between the size of farm and technical efficiency and found positive correlation.

Using Taiwanese national survey on rice farmers, Chang & Wen (2011) studied the differences in production, efficiency and risks among farmers with and without off-farm income. They estimated separate stochastic production functions for each group of farmers. Their result indicates differential relationships between off-farm incomes and technical efficiency of farmers. For instance, they found an increasing impact of off-farm income on technical efficiency for lower percentiles of the technical efficiency distribution. The authors also argue that lower scores in technical efficiency do not necessarily relate to participation in off-farm activities because of differences in the use of resources among the two groups of farmers. Accordingly, those farmers without off-farm activities were found to be more productive in the use of farm inputs than those with off-farm activities. This implies that farmers without off-farm activities have better knowledge in use of farm inputs that emanates from their concentration on farm activities. The authors also argue that higher production risks are associated with farmers participating in off-farm activities.

From the 2002 Chinese household income survey, Yue & Sonoda (2012) analyzed the impact of off-farm work on technical efficiency of farmers in three regions of the country. Their result confirms that farm household's without off-farm wage were found to be technically more efficient than those with off-farm wage. This is because households with off-farm wage do not invest their income on farm productions. Furthermore, their findings also show regional difference of the impact of off-farm wage on technical efficiency.

Similarly, Babatunde (2013), also studied the link between on-farm works and off-farm works in rural Nigeria. In his study, he examined the impact of off-farm income on farm level output, purchased inputs and technical efficiency of farmers. The finding of his research confirmed positive associations between off-farm income and output, purchased inputs and technical efficiency.

Using Instrumental variable estimation, Woldehanna (2002) examined the linkages between farm and non-farm activities in northern Ethiopia. His result indicates that non-farm income plays a vital role in reducing credit constraints of poor farmers. However, the impact of non-farm income on farm input was found negative due to unfavorable conditions in the study areas. The author also found that poor households and large families are more likeliy to participate in off-farm activities than rich households and small sized families. In general, the findings of his study indicate that non-farm income has a positive and significant effect on investments in equipment, livestock and buildings, whereas negative effects on improved seeds and fertilizer.

Iheke *,et al.* (2013) examined the impact of remittance on technical efficiency of farmers in Nigeria. They estimated separate production frontiers for farmers with and without remittance. The finding of their analysis shows that remittance- receiving farmers are less technical efficient than non-remittance receiving farmers. Remittance- receivers were found to have a mean technical efficiency of 42 percent, whereas non- receivers have a mean technical efficiency of 53 percent. They also indicated that efficiency of non-recivers is related to educational level of the head of household, size of household, size of farm land and farming experiances, whereas that of remittance- receivers mainly relates to age of the head of household and size of farm land.

Pfeiffer *,et al.* (2009) studied the impact of off-farm income on agricultural production in Mexico; specifically, they anlyzed the impact of off-farm income on household production, input demand and technical efficiency. They regressed farm production against off-farm income and other explanatory variables. The authors also adopt an instrumental variable approach to handle the problem of endogeneity of off-farm income. The findings of their study indicate that off-farm income is negatively associated with value of agricultural output and family labour used in agricultural production, whereas positively associated with technical efficiency and purchased inputs. Further, the authors also indicated that mean technical efficiency of farmers with off-farm income is higher than those without off-farm income.

4. Methodology of the Study

4.1. Descrtiption of study areas and data

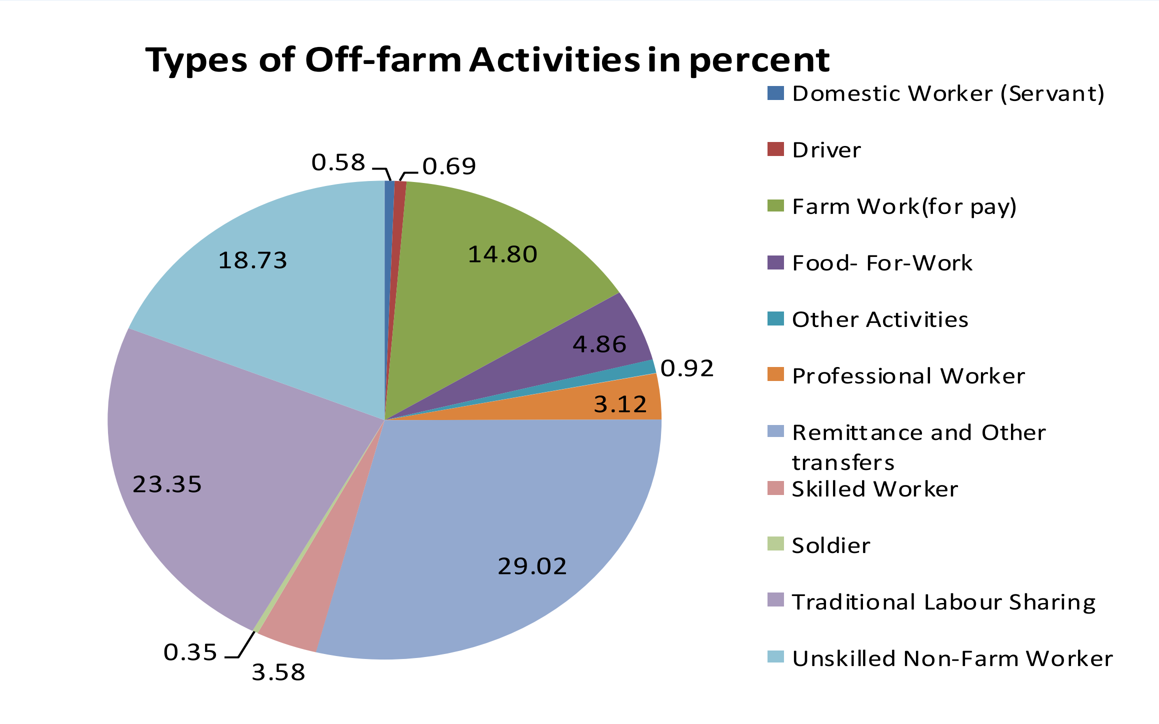
With an estimated population of more than 90 million, Ethiopia is the second most populous country in Africa. The country is located in the horn of the continent covering an area of land of 112.3 million hectares. Agriculture is the pillar of its economy, accounting for 46.3 percent in gross domestic product (GDP). Out of total land area, 16.4 million hectares are adequate for production of perennial and annual crops (Deressa, 2007). According to Dorosh and Gemessa (2013), wheat, teff[2], maize, barley and sorghum production constitutes the major food crops in the country, accounting for three-fourth of total area of land under cultivation and 14 percent of GDP. Coffee, pulses, hides, skins, oilseeds, tea, honey and beeswax are the major agricultural exports of the country.

The study uses Ethiopian Rural Household Survey (ERHS) data conducted by the Economics department of Addis Ababa University in collaboration with International Food Policy Research Institute (IFPRI) and Centre for the Study of African Economies, University of Oxford in 2009. The comprehensive survey was undertaken in four major regions of the country; Tigray, Amhara, Oromia and Southern Nation's Nationalities and People's Regional State (SNNPRS) covering larger number of peasant associations, districts, and villages in rural part of the country.

These regions represent for an estimated total land area of 52 percent and a population of 90 percent in the country. The data set mainly covers households' demographics, asset holdings, access to credit, expenditures, off-farm income and poverty aspects of the rural societies (Dercon & Hoddinott, 2004). Based on the availability of data on relevant variables, 1360 households are involved in this study. Out of the whole sample about 63.6 percent of the households participate in one or more types of off-farm income generating activities whereas the remaining 36.4 percent are non-participants. As shown figure (3), about 29 percent of farmers receive remittances, 23 percent engage in traditional labour sharing, 19 percent participates in unskilled non-farm work and 15 percent participate in paid farm works. The remaining groups participate in skilled works, paid developmental activities (such as food-for-work), professional works and other activities.

[2] Teff is an annual grass-type cereal grown in Ethiopia.

Figure 3: Types of off-farm income generating activities



Source: Own Computation

4.2. Empirical model specification

4.2.1. Production frontier and technical efficiency

The first main objective of this study is estimating a production frontier and the corresponding technical efficiency. Hence, the empirical analysis begins with estimating a production function and efficiency scores of individual households, using a stochastic frontier model. One of the main advantages of th is model is that the error term captures measurement errors, statistical noises, exogenous shocks, and contains an inefficiency component used in the statistical test for the degree of technical inefficiency of farm household.

The stochastic frontier production function can be specified as:

$$y_i = f(x_i;\beta)e^{v_i}TE_i \quad , \quad (i = 1,2,.......,1360) \qquad (6)$$

Where y_i is output of i^{th} household, x_i is vector of inputs used in the production process by i^{th} household, $f(x_i;\beta)$ is production frontier, β is a vector of frontier parameters to be estimated, e^{v_i} measures random shocks and TE_i is the technical efficiency of the i^{th} farm household.

According to Coelli ,*et al.* (2005) technical efficiency of an individual farm is the ratio of observed (actual) output to the corresponding frontier (potential) output. Therefore, technical inefficiency measures the amount by which the actual level of output falls below the frontier level. The value of technical efficiency varies between zero and one. If technical efficiency is exactly equal to one, the actual output y_i achieves its potential level $f(x_i;\beta)\exp(v_i)$. On the other hand, if technical efficiency is less than one, it implies the presence of technical inefficiency. Technical efficiency therefore can be re-written as;

$$TE_i = \frac{y_i}{f(x_i;\beta) * e^{v_i}} \quad , \text{ where } 0 \le TE_i \le 1 \tag{7}$$

Most stochastic frontier studies use either a Cobb-Douglas (CD) or Translog (TL) functional form for the production functions. In this study, both CD and TL models are specified and the most appropriate model is selected based on log-likelihood ratio tests[3]. Given different factors of production, the two alternative stochastic production frontiers are specified respectively as follows:

Cobb-Douglas: $$\ell n(y_i) = \beta_0 + \beta_i \sum_{i=1}^{5} \ell n(X_i) + v_i - u_i \tag{8}$$

Translog: $$\ell n(y_i) = \beta_0 + \sum_{k=1}^{5} \beta_k \ell n(X_{ik}) + \frac{1}{2} \sum_{k=1}^{5} \sum_{j=1}^{5} \beta_{ij} \ell n(X_{ik}) * \ell n(X_{ij}) + v_i - u_i \tag{9}$$

Where ℓn is the natural logarithms, $\beta's$ are coefficients of parameters to be estimated, y_i is the total value output in Ethiopian Birr (ETB). In fact the value of output was calculated in steps. Since all productions were measured in local units, it was first converted to standard unit, kilograms (kgs). Then, using price conversion, quantity of output was converted to ETB. $X_i's$ are factors of prductions, v_i is the idiosyncratic error that arises from measurement errors in input use and/or yield of production and u_i is the non-negative random variables in measuring the technical inefficiency of individual household.

The non-negative error term u_i assumes different distributional forms. The most commonly used distributions are half-normal, exponential, truncated-normal, and gamma distributions, each having their own assumptions and characteristics. Since there is no prior justification/reasoning in choosing one distribution over the other, all except the gamma

[3] Log-likelihood ratio test results are reported in sub section(5.2.2)

distributions are considered in this study. The gamma distribution is not included because of numerical difficulties that arise when estimating the model parameters.

For example, if it is assumed that the non-negative error term is half-normally distributed, then the marginal distribution of the composed error $\varepsilon_i = v_i - u_i$ is given as;

$$f(\varepsilon_i) = \int_0^{\infty} f(u,\varepsilon)du = \frac{2}{2\pi\sigma_u\sigma_v}\exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\}$$

$$= \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right)\left[1-\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \quad \text{for} \quad -\infty < \varepsilon_i < \infty \tag{10}$$

Where $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \frac{\sigma_u}{\sigma_v}$ are variance parameters and $\phi(.)$ is the standard probablity density function and $\Phi(.)$ is the standard cummulative density function.

According to Kumbhakar & Lovell (2003), λ in equation (10) shows the relative contribution of u_i and v_i, respectively, to ε_i. Hence, as $\lambda \longrightarrow 0$ either $\sigma_v^2 \rightarrow +\infty$ $or\ \sigma_u^2 \rightarrow 0$. In this case v_i (the symmetric error) dominates u_i(one–sided error). On the other hand, as $\lambda \longrightarrow +\infty$ either $\sigma_v^2 \rightarrow 0$ or $\sigma_u^2 \rightarrow +\infty$, u_i dominates v_i in determining ε_i.

Given the marginal distribution of the composed error in equation (10), the next step is forming and maximizing the likelihood function with respect to β, σ^2, λ to obtain the estimate of unknown parameters and consequently the measure of inefficiency, u_i. However, it is impossible to decompose the estimates of the error term, $\hat{\varepsilon}_i$, into $\hat{v}_i$ and $\hat{u}_i$. The solution is to take the conditional distribution of u_i given ε_i as it was first proposed by Jondrow ,*et al.* (1982). The conditional distribution of u_i given ε_i is therefore given as follows:

$$E(u_i \mid \varepsilon_i) = \hat{u}_i = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi\left(\varepsilon\lambda/\sigma\right)}{1-\Phi\left(-\varepsilon\lambda/\sigma\right)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \tag{11}$$

Finally, given the point estimates of u_i in equation (11), the technical efficiency of the individual household is:

$$TE_i = \exp(-\hat{u}_i) \tag{12}$$

Several empirical studies on productivity and efficiency argue that demographic, socio-economic, institutional and environmental factors attribute to efficiency differentials among farmers (Aigner *,et al.*, 1977; Battese & Coelli, 1995; Bravo-Ureta & Pinheiro, 1997; Obwona, 2006; Nyagaka *,et al.*, 2010). Following these studies and availability of data, ten variables have been used to explain efficiency differentials among households. Accordingly, demographic factors (household size, age, gender and education level of the household head), institutional factors (access to extension services, use of irrigation, manure and soil conservations practices) and resource factors (number of livestock owned and income generated from off-farm activities) are used as explanatory variables in the inefficiency model specified in equation (13):

$$U_i = \delta_0 + \sum_{i=1}^{10} \delta_i Z_i + \varphi_i \tag{13}$$

Where U_i is technical inefficiency, $\delta_i's$ are the parameters to be estimated, $Z_i's$ represent a set of explanatory variables explaining technical inefficiency. These includes, household size, age, gender and education level of the household head, soil conservation practices, use of extension services, irrigation and manure, total off-farm income of the household and φ_i is the random error term $(\varphi_i \sim N(0, \sigma_\varphi^2))$.

There are in general two methodological approaches in the estimation of inefficiency model in stochastic frontier analysis. The first approach is a one-stage procedure in which production function and sources of technical efficiency are estimated simultaneously. The second approach a two-stage estimation technique in which the stochastic production frontier and efficiency scores are estimated in the first stage and the derived efficiency scores from the first stage are regressed on a set of explanatory variables using OLS. However, this approach has been criticized because farmers' knowledge of its level of inefficiency may affect choice of inputs (Chirwa, 2007). Given these facts, estimation of technical efficiency scores and determinants of inefficiency will be estimated based on one-stage estimation technique.

List of explanatory variables and expected signs

Labour (X_1): is total number of family and hired labourers used in different stages of production such as land prerpartion, planting and general cultivation and harvesting.

Land (X_2): is total area of land used for main crop production in hectare (ha). Land is the most important input in smallholder production. In this study, land refers to the total area of farm land used for main crop production. It doesn't include marginal, set aside lands and grazing lands.

Fertilizer (X_3): is the total amount of modern fertilizers used in kgs.

Farm instruments (X_4): is number farm equipment such as ploughs, hoes, sickles and other farm instruments owned by the household.

Oxen (X_5): is total number of oxen owned by the household.

In general, several studies have shown positive association between inputs and output in production. This implies that households with more inputs are expected to produce more output. Therefore, positive association between the dependent variable (value of output) and all explanatory variables (inputs) is expected.

Age(Z_1): is an indication of experience and capacity of the household in agricultural operations. Emprical studies for example Tan *,et al.* (2010) and Etim and Okon (2013) argue that older households are more experienced than younger ones. Therefore, age is expected to have positive impact on farm output and the level of technical efficiency of the farmer.

Household Size(Z_2): represents the number of household members. In smallholder production the size of household is a means to have more supply of labour. Hence, the larger the household size the higher level of production they produce and the higher technical efficient they will be. Hence, size of the household is expected to have positive association between production and technical efficiency of the farmer.

Gender of HH Head (Z_3): is a dummy variable representing the gender of household head taking a value of 1 for male headed households and 0 for female headed households. Even though women play a substantial role in agricultural activities, there are still tasks that are not done by women for example ploughing. Hence, male headed households are expected to be more efficient than female headed households. Besides, female headed households may also have to perform additional tasks such as taking care of children and therefore they may have to allocate their time between these tasks and actual farm activities.

Education (Z_4)*:* indicates the years of schooling of the household head. Education is usually an indication for quality of labour. It is argued that educated (skilled) farmers to have better skills of managing farm operations and understand new technologies that increase their production. Hence, education is expected to be positively associated with farm output and the level of technical inefficiency of the farmer.

Livestock owned (Z_5)*:* agricultural productivity can also be affected by the number of livestock owned by the farmer. Besides their use in different stages of agricultural activities, revenues from selling livestock supplement farm income in case of a crop failure. Hence, those farmers owning more livestock are expected to be more technically efficient.

Soil conservation (Z_6)*:* households practice different soil conservation mechanisms to sustain the productivity their farm land. It is obvious that conserved farm land produces more output than non-conserved lands. Hence, those households practicing soil conservation are expected to be more technically efficient. Soil conservation is a dummy variable that assumes 1 if the farmer conserve soil and 0 otherwise.

Extension Services (Z_7)*:* is a dummy variable taking values of 1 if an extension expert visits the farmer and 0 otherwise. Those households who are visited by extension experts are expected to have more information which enables them to produce efficiently. Hence, the impact of extension services on the level of efficiency is expected to be positive.

Use of irrigation (Z_8)*:* is a dummy variable that assuming 1 if the farmer uses irrigation and 0 otherwise. Basically, the majority of the farmers in Ethiopian practice rain-fed agriculture and productions are usually once a year in most parts of the country. Hence the use of irrigation increases total output produced in a given year. Irrigation is therefore expected to have a positive impact on production and technical efficiency of farmers.

Use of Manure (Z_9)*:* is a dummy variable assuming 1 if the household uses manure and 0 otherwise. Studies indicate that, those households using manure are more efficient in production than those who are not using manure. Hence, it is hypothesized that farmers using manure are more efficient than others.

Off-farm Income (Z_{10})*:* off-farm income is the variable in the main focus in this study. It represents total income generated from any type off-farm activities including remittances. As explained in earlier sections, the relationship between off-farm income and level of technical efficiency is quite unclear. Off-farm income enhances the production and productivity of farmers if incomes from off farm activities are spent as investment in farming sector, whereas participation in off-farm activities have negative effects on farm activities when off-farm incomes are used for consumption or investment in other sectors. Existing evidence such as Beyene (2008) reveals that Ethiopian farmers usually participate in off-farm activities mainly to overcome their liquidity constraints. Hence, Off-farm income is expected to positively impact on their farm production and on the level of technical efficiency.

4.2.2. Off-farm income and Farm output

Off-farm income has direct and indirect effects on agricultural production. The direct effect is related to the absence of labour (lost-labor effect) in farm operations; whereas, the indirect effect is related to the investments of off-farm income on farm activities (López-Feldman *,et al.*, 2007).

The impact of off-farm income on the value of farm outcome can be analyzed by comparing output of recipents of off-farm income and non-recipents, while controlling other factors.Thus, systematic difference among the two groups of farmers are captured through the inclusion of explanatory variables on household characteristics (Kilic *,et al.*, 2009). Accordingly, following, López-Feldman *,et al.* (2007), Kilic *,et al.* (2009) and Babatunde (2013), the value of farm output is regressed against off-farm income and other explanatory variables and the model for farm outcome is specified as follows:

$$Y_i = \beta_0 + \beta_1 OI_i + \beta_i \sum_{i=2}^{6} X_i + \varepsilon_i \qquad (14)$$

Where Y_i the value of farm output is, $\beta's$ are parameters to be estimated, OI_i is off-farm income and $X's$ are a set of variables on household characteristics and resource factors mentioned above in section $(4.2.1)$. This includes, household size, age, gender, education level and marital status of the household head, size of farm land, and ε_i is the error term.

The impact of off-farm income on farm outcome is therefore determined based on the estimated coefficient of off-farm income in equation (14). However, studies on the linkage of farm and off-farm income, for example Babatunde (2013), indicates the possibilities where productivity of farming sector depends on off-farm income and vice versa. Thus, there might be reverse causality problem that leads to endogeneity bias. In fact, endogeneity test confirms the presence of endogeneity problems in the model. As a result, the OLS method results in biased estimates for unknown parameters. Therefore, instrumental variable regression framework is introduced to overcome this problem. Accordingly, off-farm income is instrumented by other proxy variables such as access to credit, radio and distance from the nearest town.

As evidenced by some studies for example Woldehanna (2002),Beyene (2008), Babatunde *,et al.* (2010) and Babatunde (2013), income from off-farm activities is also determined by the availability of credit, access of new information and distance to the nearest town besides household characteristics and resource factors. Theoretically, access to credit and radio or related telecommunication technologies should have a positive effect on off-farm activity participation, while distance from the nearest town has a negative impact. Therefore, positive association between off-farm income and access to credit and radio is expected; whereas negative association between distance from the nearest town and off-farm income is expected.

4.2.3. Estimation Technique

Because of the non-negativity assumption of the inefficiency term (u_i), the underlying distribution is non-normal and the error terms are therefore asymmetrically distributed. Hence, the ordinary least squares (OLS) estimator is inefficient. Coelli (1995) argues that there are two main benefits of using frontier functions as the ones in equation (8) and (9), rather than OLS (average functions). First, frontier functions are based on best performing producers and therefore can show the technology used in production, whereas average fucntions only shows technology of an average producer. Secondly, frontier functions show the best-practicing technology, whereas average functions show efficiency of producers within the whole group. Schmidt & Knox Lovell (1979) also argued that MLE technique provides more efficient estimates than the OLS, besides its guarantee of non-negativity assumptions on the error terms. Thus, unknown parameters of frontier models are estimated using the maximum likelihood estimation (MLE) technique

5. Result and Discussion

5.1. Descriptive Statistics

As shown in the summary statistics in table (2), the average age of household in the whole sample is 52 years. Male headed households' accounts for 67 percent of the whole sample. This implies that on average about 67 percent control and management of agricultural resources and activities are male's responsibility. Besides, 69 percent of the surveyed households are married.

Table 2: Summary statistics of model variables

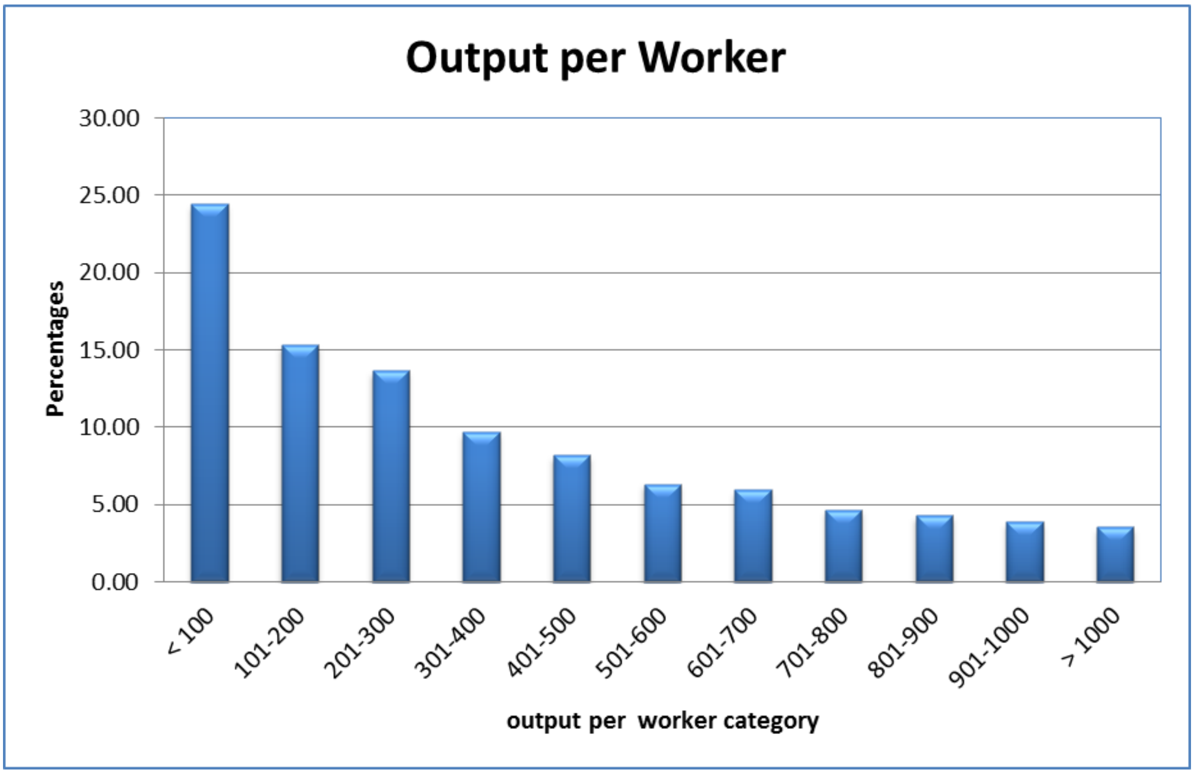
Variables	Mean	Sta.Dev.
Age (Years)	52.212	14.71
Male headed HH (Dummy, 1 if male & 0 otherwise)	0.67	0.47
Household size (Number)	5.71	2.55
Education (Years of schooling)	1.94	2.89
Married (Dummy, 1 if married& 0 otherwise)	0.69	0.46
Output (ETB)	6086.24	6480.57
Land(Ha)	0.56	0.647
Labour(Number)	14.69	19.42
Oxen(Number)	1.13	1.34
Livestock(Number)	5.34	5.76
Farm equipment (Number)	11.85	8.92
Fertilizer(Kg)	74.68	125.93
Off-farm income	1418	3836
Use of irrigation(Dummy, 1 if s/he uses& 0 otherwise)	0.10	0.31
Soil conservation(Dummy, 1 if s/he conserves& 0 otherwise)	0.504	0.50
Access to extension services(Dummy, 1 if s/he have & 0 otherwise)	0.48	0.50
Use of manure(Dummy,1 if s/he uses& 0 otherwise)	0.07	0.26
Access to Credit(Dummy,1 if s/he have& 0 otherwise)	0.57	0.49
Association membership(Dummy,1 if s/he is & 0 otherwise)	0.15	0.35
Access to radio(Dummy,1 if s/he has& 0 otherwise)	0.58	0.49
Access to cellphone(Dummy, 1 if s/he has& 0 otherwise)	0.11	0.31
Distance from the nearest market/town (kilometers)	10.25	5.68

Source: Own Computation

The average schooling years of the farm household is 2 years. The mean value of output is 6086.24 ETB. Regarding farm inputs, the average values are 0.56 hectares of land, 15 Labourers, 12 units of farm equipment, 5 livestock and 75 kilograms of fertilizers. The average off-farm income of the household is 1418 ETB. Use of extension services, irrigations and manure among farmers accounts for 48, 10 and 7 percent respectively. About 50 percent households in the survey sites practice soil conservation. On the other hand, 57 percent of households have access to credit and 51 percent have access to either radio or tape whereas only 11 percent of farmers have access to cellphone. In addition, 15 percent of the households are members of one or more association. The average distance from the nearest town/market is about 10 kilometers.

As presented in table 2, the highest value standard deviation of value of output (i.e. 6480.57) shows the degree of variation in output level in the sample. In fact, the distributions of output per worker and output per hectare also confirm the variability of output. As shown in figure 4, about 24 percent of sampled farmers have output per worker less than 100. About 72 percent of farmers have output per worker between 100 and 1000; whereas, the remaining 4 percent of sampled farmers have output per worker greater than 1000.

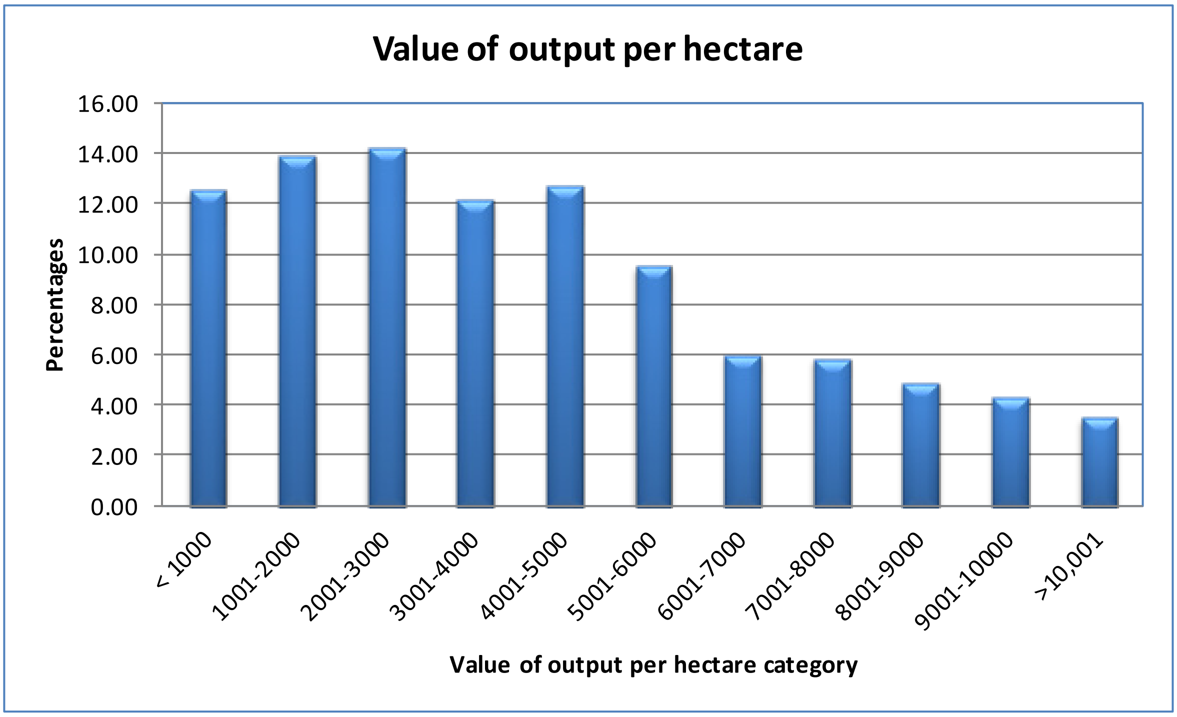
Figure 4: Distribution of output per worker



Source: own computation

Similarly, output per hectare also shows substantial variation across the sampled farmers. As presented in figure 5, about 13 percent of the farmers have output per hectare less than 1000. The majority of the farmers (i.e. 84 percent) have output per hectare between 1000 and 10000. The remaining 3 percent of farmers have output-per hectare greater than 10000.

Figure 5: Distribution of output per hectare



Source: own computation

5.2. Econometric Results

5.2.1. OLS Estimates of Production Frontier

The production function in equation (8) is first estimated using OLS to identify potential inputs that will be included in maximum likelihood estimation of production function. The estimation result indicates that 80 percent of variation in output is explained by inputs of production; *land*, *labour*, *fertilizer*, *oxen* and *farm equipment*.

As reported in table (3) *land*, *fertilizer*, *labour* and *oxen* are significant at 1 percent significance level and use of *farm equipment* is significant at 5 percent. Besides, the presence of multicollinearity and heteroskedasticity is checked using variance inflation factors (VIF) and the Breusch-Pagan test, respectively. The test result confirms that there are no multicollinearity and heteroskedasticity problems in the model. Hence, all inputs are included in the maximum likelihood estimation of production function.

Table 3: OLS estimates of CD production function: The dependent is log of Value of Output

Variables	*Coefficients*	*P>|z|*
Constant	*6.63**	*0.000*
$\ell n(labour)$	*0.10**	*0.005*
$\ell n(land)$	*0.73**	*0.000*
$\ell n(fertilizer)$	*0.13 **	*0.000*
$\ell n(farm\ equpment)$	*0.17***	*0.012*
$\ell n(oxen)$	*0.29**	*0.000*
R-squared /Adj. R-squared	*0.8015 / 0.7947*	
No. of Observation	*1360*	

** p< 0.01, ** p < 0.05,* *Source: Own Computation*

5.2.2. Test for Model Specifications

Before estimating model parameters using the MLE method, testing specification and validity of the model is a vital task. Thus, the following hypotheses are tested to identify the appropriate functional form and estimation method for the dataset in scope. The first hypothesis aims at testing the adequate functional form. Accordingly, both CD and TL[4] production functions in (8) and (9) are estimated using maximum likelihood estimation method followed by a log-likelihood ratio test (LR test) to choose the most appropriate production function. The generalized LR test statistic is given as:

$$\lambda = -2\ell og[L(H_0)/(H_1)] = -2\{\ell og[L(H_0)] - \ell og[L(H_1)]\}$$

Where $\ell og[L(H_0)]$ and $\ell og[L(H_1)]$ are values of likelihood functions under null hypothesis H_0 (CD function) and alternative hypothesis H_1 (TL function) respectively. In this test, we reject the null hypothesis when the value of the calculated likelihood ratio exceeds the critical likelihood ratio (χC^2). The value of calculated LR equals to 17.08, 15.93 and 16.50 in half-normal, exponential and truncated-normal respectively; while the critical LR at upper 5 percent level of significance and 15 degrees of freedom $(\chi C^2{}_{0.05,15})$ is equal to 24.99 as published in the article of Kodde & Palm (1986). Given these values, we cannot reject the null hypothesis that states that coefficient values of all interaction and

4 MLE estimate of TL function is presented in appendix (2).

second order terms of the TL production function are equal to zero. Hence, the Cobb-Douglas production function is more appropriate in representing the data. This study is therefore based on estimation results from the CD form of the production function. One of the main advantage of the CD form is the ease at which returns to scale can be measured. Thus, the return to scale can be constant, decreasing or increasing based on the sum of exponents (Neumann *,et al.*, 2010).

The second hypothesis is checking whether the stochastic production frontier is more appropriate than a conventional production function, i.e. testing whether there exists technical inefficiency in the production process or not. In this test the null hypothesis is given as $H_0 : \gamma = \delta_1 = \delta_2 = ... = \delta_{10} = 0$ where $\gamma = \sigma_u^2 / \sigma^2$ and $0 \leq \gamma \leq 1$. The closer the value of γ is to zero, the more likely OLS represent the data and the closer the value of γ is to one, the more likely a stochastic frontier model represent the data best (Piesse & Thirtle, 2000). Accordingly, the value of γ in the CD function is 0.878, 0.667 and 0.985 in half-normal, exponential and truncated-normal models respectively. This implies that farmer's technical inefficiency accounts for 88 percent, 67 percent and 99 percent in the variations of actual output from its potential level in the respective models. Likewise, the value of γ in the TL function is 0.851, 0.615 and 0.844 in half-normal, exponential and truncated-normal distributions respectively. Given these values the null hypothesis is rejected confirming the presence of technical inefficiency in the data set.

On the other hand, the choice of the estimation method to be adopted can also be checked based on the skewness of residuals from the OLS regression. Thus, if the third moment is negative, then OLS residuals are negatively skewed, indicating the presence of technical inefficiency. In contrast, positive skewness of the third moment suggests the absence of inefficiency which in turn implies the appropriateness of the OLS method in the estimation of model parameters (Waldman, 1982; Kumbhakar & Lovell, 2003; Van Keilegom & Wilson, 2012). Given these facts, the kernel density estimates of residuals of the OLS regression presented in appendix (3) showed negative skewness. This implies that the maximum likelihood estimation method provides more consistent estimates than ordinary least squares.

Besides, identifying the most representative model among the three distributions (i.e. half-normal, exponential and truncated-normal distributions) is the basic task. According to Greene (2005), a distribution with relatively smaller variance is more representative. Thus, comparing the kernel density[5] plots of efficiency scores of the three models, exponential model is more representative than the other two models. Half-normal and truncate-normal models cannot represent the data because of higher variance in the half-normal model and statistically insignificance of variance component (σ_u) and inefficiency indicator lambda (λ), in truncated model as shown in table 4. Hence, estimation of determinants of technical efficiencies is based on exponential model.

5.2.3. MLE Estimates of Production Frontier

The MLE estimates of CD production function based on the three distributional assumptions is presented in table (4). The result shows that all inputs are positive and statistically significant at 1 percent in all the three models. The log likelihood values of the distributions are also similar. Lambda (λ), an indicator of the presence of inefficiency, is greater than zero and significant at 1 percent in half-normal and exponential models and insignificant in truncated model. Besides, variance components σ_u and σ_v are also significant at 1 percent significance level in half-normal and exponential models.

However, the values of σ_u and μ are found insignificant in truncated-normal. This implies that deviation of output from its frontier output is because of statistical noise. In reality however, there is always a deviation of output from its potential level in any production process, which entails the contribution of the inefficiency term error (σ_u) in the total error.

On the other hand, the mean technical efficiency is closely similar in exponential and truncated-normal distributions whereas relatively smaller in the half-normal model. The mean technical efficiency of households is 42.7, 52.9 and 52.1 in half-normal, exponential and truncated normal, respectively. In fact, Technical efficiency is a relative concept and these values imply that farmers are on average 43, 53 and 52 percent efficient compared to the most efficient farmer in the respective models. In general, the values are consistent with the study by Asefa (2012), Geta *,et al.* (2013) and Tirkaso (2013).

[5] kernel density plots of the three distributions are presented in appendix (3)

Table 4: MLE estimates of production function in half-normal, exponential and truncated models

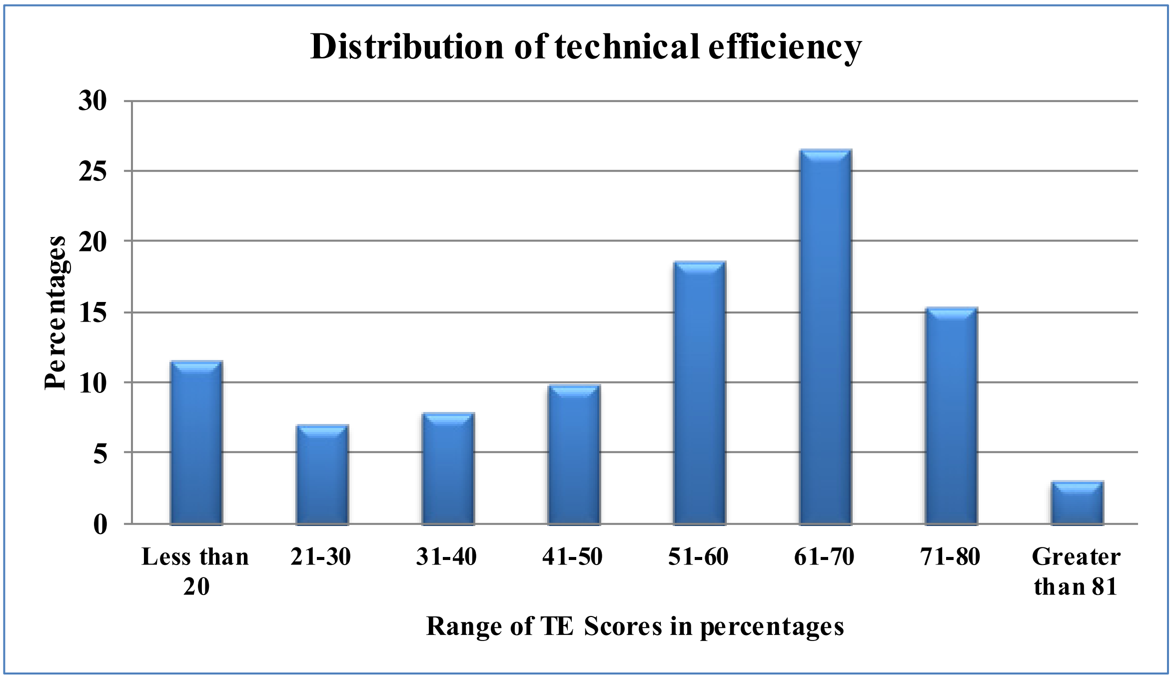
Variables	Half-Normal		Exponential		Truncated-Normal	
	Coeff.	$P>\|z\|$	Coeff.	$P>\|z\|$	Coeff.	$P>\|z\|$
Constant	7.510*	0.000	7.19*	0.000	7.222*	0.000
$\ell n(labour)$	0.085*	0.007	0.078*	0.006	0.078*	0.006
$\ell n(land)$	0.824*	0.000	0.951*	0.000	0.937*	0.000
ℓn (fertilizer)	0.108*	0.000	0.111*	0.001	0.111*	0.001
$\ell n(farm\ equpment)$	0.152*	0.005	0.145*	0.004	0.145*	0.003
$\ell n(oxen)$	0.227*	0.000	0.207*	0.000	0.209*	0.000
sigma_u	1.314*	0.001	0.781*	0.003	4.389	0.130
sigma_v	0.488*	0.000	0.551*	0.000	0.544*	0.000
lambda	2.683*	0.004	1.416*	0.000	8.066	0.110
Mu	-		-		-22.453	0.160
Log-Likelihood	-1732.545		-1723.195		-1723.010	
Mean TE	0.4271		0.5299		0.5208	
No. of Observation	1360		1360		1360	

** p< 0.01 , Source: Own Computation*

5.2.4. Distribution of technical efficiency

The estimated result shows a higher variation in technical efficiency score among farm households. As presented in the summary of technical efficiency in appendix (5), the technical efficiency of farm households ranges from a minimum score of 14 percent to a mximum score of 89 percent. As shown in figure (6), about 12 percent of the households have an efficiency score less than 20 percent. Whereas, 25 percent of farm households have efficiency score between 20 and 50 percent.The majority of the household (i.e. about 60 percent) have efficiency score between 50 and 80 pecent. Only 3 percent of farm households have efficiency score gretare than 80 percent. In general, such a wider variation in efficiency scores indicates farmers' inefficiency in utlilizing their resources; which further implies the existence of wider scope for improvement of their efficiency.

Figure 6: Distribution of technical efficiency



Source: Own Computation

5.2.5. Elasticity of factors of production

The estimated elasticity[6] of output with respect to labour, land, fertilizer, farm equipment and oxen in this model is 0.08, 0.95, 0.11, 0.15 and 0.21 respectively. This implies that, keeping all othr inputs constant, a 1 percent increase in hectares of *land*, the number of *labour*, *farm equipment*, *oxen* and kilograms of *fertilizer* leads to 0.08, 0.95, 0.11, 0.15 and 0.21 percent in the level of output. The result confirms that *land* is the most important input followed by number of *oxen* owned by the household.

Furthermore, the sum of elasticity of all inputs is greater than one, indicating that production function exhibits increasing returns to scale. Thus, a proportional increase in all inputs would increase output more than the proportional increase in the inputs. Such an increasing return to scale is also confirmed by Chirwa (2007) and Asefa (2012). In other words: Increasing inputs beyond the current level is still beneficial which implies that the farmers in the sample should grow and use all inputs more intensively.

5.2.6. The effect of off-farm income on technical efficiency

This section presents estimation results of the inefficiency model specified in equation (13). As explained in section 4.2.1, it is not possible to use instruments for endogenous variables (off-farm income) in the single-stage estimation that simultaneously estimates the stochastic production frontier and the efficiency model. Therefore, predicted value of off-farm income

[6] The estimated elasticities are based on exponential model presented in table 4.

from the first-stage estimation of off-farm income regression in section (5.2.7) is used to address problem of endogeneity in the estimation of determinants of technical efficiency.
The MLE results of the inefficiency model (as presented in table 5) show that all explanatory variables except use of *irrigation* and *manure* have the expected sign. However, *age* and number of *livestock* owned are not statistically significant implying their small/nil importance in improving the technical efficiency of households. All other variables are in line with prior hypothesis discussed in the third chapter. Accordingly, *household size, education* of the head*, off-farm income*, *soil conservation* and *extension services* are significant at 5 percent while *gender* of the household head is significant at 10 percent.

Besides, the coefficient of *household size* also shows a positive association between *household size* and technical efficiency. This implies that households with larger family size are more efficient; indicating their higher possibilities of having larger labour supply during peak agricultural seasons. This result is consistence with Obwona (2006), Msuya *,et al.* (2008) and Al-hassan (2012).
Educational level of the household head is also positively associated technical efficiency. In fact, education is usually considered as an indication of higher possibilities of literate households in having better managerial skills, access and understanding of information on improved methods to their farm operations. Thus, households with more schooling years are more technically efficient. Such association between education and technical efficiency is also confirmed by Battese & Coelli (1995), Liu & Zhuang (2000), Khai & Yabe (2011) and Tirkaso (2013).
Gender of the household head has a positive impact on the level of technical efficiency. This means that male headed households are more technically efficient than female headed households. Msuya *,et al.* (2008) also found the same correlation between gender of the household head and technical efficiency.
The coefficient of *soil conservation* reveals positive association between conservation practices and technical efficiency. According to Jara-Rojas *,et al.* (2012), soil conservation practices not only increase production and productivity of farm land, but also enhances environmental sustainability. Similarly, Solis *,et al.* (2007), also found positive correlation between soil conservation practices and technical efficiency in their studies on the level of technical efficiency under different degrees of soil conservation practices in Central America.

Table 5: MLE estimates of determinants of technical inefficiency: The dependent variable is technical inefficiency

Variables	*Coeff.*[7]	*P>|z|*
Constant	*-1.38**	*0.001*
Z_1 (Age)	*-0.17*	*0.180*
Z_2 $(HH\ Size)$	*-0.23***	*0.041*
Z_3 $(Gender)$	*-0.14****	*0.072*
Z_4 $(Education)$	*-0.16***	*0.035*
Z_5 $(Livestock)$	*-0.15*	*0.130*
Z_6 $(Soil\ Conservation)$	*-0.36***	*0.023*
Z_7 $(Extension\ Services)$	*-0.09***	*0.037*
Z_8 $(Irrigation)$	*0.35*	*0.240*
Z_9 $(Manure)$	*0.04*	*0.160*
Z_{10} $(Off-farm\ Income)$	*-0.48***	*0.029*
Log likelihood	*-1455.2437*	
No of Observation	*1360*	

* *p< 0.01, ** p < 0.05 , *** p < 0. 10 , Source: Own Computation*

Extension services provided to households plays crucial role in creating capacities to improve overall performances of farm productions through access to better information on new technologies. The estimated coefficient of extension services in this study also confirms the positive impact of extension services on technical efficiency of farmers. Similar effects of extension on technical efficiency of farmers are also reported in other studies by Obwona (2006), Binam ,et al. (2008) and Nyagaka ,et al. (2010).

Off-farm income is the most primary variable of analysis of this study. According to Amare (2005),off-farm incomes can have positive effect on the households' efficiency by alleviating financial constraints in terms of timely purchase of farm inputs. On the other

[7] A negative value of estimated coefficients implies an increase in the level technical efficiency.

hand, participating in off-farm activities might be at the expense of own farm activities in terms of less labour and time causing for a negative relationship between technical efficiency and participation in off-farm activities. In this study, the estimated coefficient of off-farm income shows a positive and significant association between off-farm income technical efficiency. This implies that an increase in off-farm income increases the technical efficiency of farmers. Such a positive association between the two variables is also reported in other studies by Rizov *,et al.* (2001), Alene & Hassan (2003b) and Bojnec & Ferto (2011). However, it is against the studies by Kumbhakar *,et al.* (1989), Singh *,et al.* (2009) and Geta *,et al.* (2013) who found negative correlations; and Chang & Wen (2011) who confirmed differential effects of participation in off-farm activity on technical efficiency of farm household.

5.2.6.1. Sensitivity Analysis

Separate production frontiers for farmers with off-farm and without off-farm income are estimated to further explore the effects of off-farm income on the technical efficiency. The result indicates that farmers with off-farm income have higher mean technical efficiency than those without off-farm income. As shown in table 6, the mean technical efficiency is 58 percent for farmers with off-farm income and 51 percent for those without off-farm income. The estimated elasticities of factors of production are slightly higher for farmers with off-farm income than those without off-farm income. Specifically, the elasticity of output with respect to fertilizer and farm equipments is for those farmers with off-farm income.This may show the inverstment of income from off-farm income on farm inputs.

In addition, the mean technical efficiency of farmers increases with the increases in off-farm income. Accordingly, the first 25% least efficient farmers have a mean technical efficiency of 38 percent with an average off-farm income of 1739 ETB. On the other hand, the second 25% least efficient groups have a mean technical efficiency of 49 percent with an average of off-farm income of 2258 ETB. The top 25 percent most efficient farmers have a mean technical efficiency of 79 percent with a mean off-farm income of 2616 ETB.

Table 6: Production frontiers[8] of farmers with and without off-farm income

Variables	*With Off-farm Income*		*Without off-farm Income*	
	Coeff.	*P>|z|*	*Coeff.*	*P>|z|*
Constant	*6.672**	*0.000*	*7.405**	*0.000*
$\ell n(labour)$	*0.152***	*0.039*	*0.046***	*0.036*
$\ell n(land)$	*0.978**	*0.000*	*0.920**	*0.000*
$\ell n(fertilizer)$	*0.138**	*0.000*	*0.096**	*0.000*
$\ell n(farm\ equpment)$	*0.182***	*0.023*	*0.152***	*0.039*
$\ell n(oxen)$	*0.202***	*0.015*	*0.201***	*0.027*
sigma_u	*0.705**	*0.000*	*0.839**	*0.000*
sigma_v	*0.528**	*0.000*	*0.556**	*0.000*
lambda	*1.333**	*0.000*	*1.509**	*0.000*
Log-Likelihood	*-858.894*		*-890.575*	
Mean TE	*0.5786*		*0.5104*	
No of Observation	*698*		*662*	

* $p< 0.01$, ** $p < 0.05$, *Source: Own Computation*

5.2.7. Effects of off-farm income on farm output

Before estimating the effects of off-farm income on farm output, endogeneity of off-farm income is checked using Durbin-Wu-Hausman test and the test statistic[9]confirmed endoginity of off-farm income. Therefore, testing the relevance and exogeneity of instruments is an important task in IV regression. *Firstly,* instruments are said to be relevant if they are correlated with the endogenous variable and at least one of the instruments have a coefficient value significantly different from zero. The following table presents first-stage estimation results of off-farm income specified in equation (14) to show the relevance of instruments. The estimation result shows, all instruments (*Access to credit*, *radio* and *distance from the nearest town*) are statistically significant in determining off-farm income.

[8] The production frontiers are based on exponential distribution and estimation results of half-normal and truncated-normal distributions are presented in appendix 6 and 7 for both groups of farmers respectively.

[9] The Durbin-Wu-Hausman test statistic $\chi 2$ test has a value of 0.762 with p-value of 0.006.

Table 7: First-stage estimates of off-farm income: the dependent variable is off-farm income

Variables	Coefficient	$P>\|z\|$
Constant	-468.10**	0.018
Household size	102.26**	0.026
Age	17.88	0.160
Gender	570.39	0.220
Educational level	134.32***	0.076
Martial status	60.89	0.127
Farm land	-301.38**	0.015
Access to credit	406.05**	0.022
Access to radio	289.66***	0.089
Distance from the nearest market	-439.47*	0.000
R-Squared/Adj. R-Squared	0.8422 / 0.8301	
Number of Observation	1360	

** p< 0.01, ** p < 0.05 , *** p < 0. 10 , Source: Own Computation*

Accordingly, *accesses to credit* and *radio* have positive impact in determining income from off-farm activities while; *distance from the nearest town* has negative impact on off-farm income. On the other hand, other variables, such as *size of the household*, the level of *education* of the head and *farm land* are found statistically significant with prior expectation while *age* and *marital status* are found insignificant.

As shown in table (7), larger families tend to generate more income from off-farm activities than small-size families. Thus, keeping all other variables constant, having an additional family member increases off-farm income by 102 ETB. Similarly, an additional years of *schooling* increases off-farm income by 134 ETB. *Access to credit and access to radio* also increases off-farm income by 406 and 290 ETB respectively. *Size of farm land* and *distance from the nearest town* however decreases off-farm income by 301 and 439 ETB respectively. The argument for these is that, those households owning larger farm lands are more likely to concentrate on farm activities than participating in off-farm activities. Besides, households with longer distances from the nearest town are less likely to earn off-farm income because of lower possibilities of participation in off-farm activities. In general, these results are in line with prior expectation and consistent with other studies by Babatunde (2013), Beyene (2008) and Ibekwe *,et al.* (2010).

Secondly, instruments are said to be exogenous if they are uncorrelated with the error term. The Sargan test for over identification is used to test the validity of instruments. In this test the null hypothesis states that over identifying restrictions are valid and therefore rejection of the null shows invalidity of the instruments. Given these facts, the Sargan $\chi 2$ has a value of 4.27 with p-value of 0.48 implying the insignificance of over identifying restrictions. Thus, the null hypothesis cannot be rejected and the instruments are therefore not correlated with the error term.

Table (8) presents the two stages least square (2SLS) estimates of farm output. The estimation result indicates that *gender*, level of *education*, *farm land* and *off-farm income* are statistically significant in determining farm output. Accordingly, the positive coefficient of *gender* indicates that male headed households produce higher output than female headed households. Consequently, keeping all other variables constant; being male household head increases farm output by 119.21 ETB.

Table 8: 2SLS estimates of farm output: the dependent variable is value of farm output

Variables	Coefficient	*P*>|*z*|
Constant	6103.05*	0.000
Household size	119.21	0.173
Age	42.35	0.152
Gender	97.53**	0.014
Educational level	12.21***	0.069
Martial status	74.27	0.193
Farm land	1442.21**	0.025
Off-farm Income	14.25**	0.019
R-Squared/Adj. R-Squared	0.5622/0.5501	
Number of Observation	1360	

Instrumented: Off-farm Income

Instruments : Household size, Age ,Gender, Educational level, Martial status, Farm land, Access to credit, Access to radio and Distance from the nearest town

** p< 0.01, ** p < 0.05 , Source: Own Computation*

The coefficient of *education* is also found positive and statistically significant in determining the value of farm output. This indicates the fact that educated farmers have better capacities of using modern inputs in their productions. Therefore, every additional year of schooling will increases farmer's output by 12.21 ETB. Furthermore, the effect of *off-farm income* on farm output is also positive and every additional ETB of off-farm income increases farm output by 14.25 ETB. In addition, the coefficient of *land* showed a positive and significant effect on farm output. In fact, *land* is the most important input in smallholder's production. Thus, an additional hectare increase in the size of farm land increases farm output by 1442.21 ETB.

6. Conclusion and Policy Recommendation

This study mainly focused on the analysis of the relationship between off-farm income and technical efficiency of smallholders in Ethiopia. The study used a stochastic frontier model in the derivation of individual efficiency scores and estimation of factors determining technical efficiency in smallholder farming. The Cobb-Douglas form of the production function was found to be more appropriate in representing the data than the translog. Positive elasticities of output with respect to *land*, *labour*, *fertilizer*, *farm equipment* and the number of *oxen* revealed the importance of these inputs in smallholders' production.

Three distributions, namely half-normal, exponential and truncated-normal distributions are considered to represent the inefficiency error term. The estimation results show that the mean technical efficiency of farmers is 43 percent, 53 percent and 52 percent in each model, respectively. In fact, these figures are in line with some studies in the area of technical efficiencies in the country. Besides, the test for inefficiency effects reveals the existence of inefficiency among the surveyed farmers; that necessities the use of frontier models.

Variables on demographic, institutional and resource factors were used to explain technical efficiency differentials among farmers. An instrumental variable regression framework was used to address the problem of endogeneity of off-farm income in determining the farm-output and the degree of technical inefficiency respectively. Accordingly, off-farm income is instrumented by proxy variables such as *access to credit*, *radio* and *distance from the nearest town*.

Maximum likelihood estimation results show that all explanatory variables except use of *irrigation* and *manure* have the expected sign. However, *age* of the household head and number of *livestock* owned are not statistically significant. All other variables are in line with prior hypothesis. Thus, efficiency of the farmers mainly related to demographic characteristics such as *household size*, years of *schooling* and *gender* of the household head; *extension services*, *soil conservation practices* and *off-farm income.* Accordingly, the *size of the household* is positively associated with technical efficiency.This implies that households' with larger families are more efficient; indicating their higher possibilities of having larger labour supply during peak agricultural seasons.

Education of the household head and *extension services* are also positively associated with technical efficiency of farmers.

The effect of *off-farm income* on technical efficiency and farm output is positive. The result of empirical analysis shows that a one ETB increase in *off-farm income* increases farm output by 14.25 ETB. Similarly, the MLE estimation result of the inefficiency model also confirms the importance of off-farm income in improving the level of technical efficiency of farmers. Accordingly, the mean technical efficiency of farmers with off-farm income is 58 percent whereas, those without off-farm income is 51 percent. This shows spillover effects of off-farm income on on-farm activities; possibly as investment on modern inputs that enhances farm production.

In general, the technical efficiency of farmers varies from 14 to 89 percent. This indicates that there is wider room/scope of increasing the productivity of the farrmers.Therefore, stakeholders in governmental and non-governmental organizations should (1) invest more on farmer's education and extension services; (2) put strong efforts towards soil conservation practices and (3) diversification of off-farm activities to improve production, efficiency and wellbeing of farmers. Finally, further research that considers the effect of off-farm income on farm operations over time is needed.

Appendices

Appendix (1): Sample size distribution across survey sites and regions

Survey Sites (Pa)	Region	Observations	Percent
Adado	SNNPRS	125	9.19
Adele	Oromia	84	6.18
Aze Deboa	SNNPRS	73	5.37
Bako Tibe	Oromia	72	5.29
Debre Berhan	Amhara	157	11.54
Dinki	Amhara	64	4.71
Doma	SNNPRS	56	4.12
Gara Godo	SNNPRS	84	6.18
Geblen	Tigray	19	1.40
Haresa	Tigray	26	1.96
Imdibir	SNNPRS	60	4.41
Korode	Oromia	103	7.57
Oda Dawata	Oromia	43	3.16
Shumsha	Amhara	106	7.79
Sirban	Oromia	72	5.25
Somodo	Oromia	74	5.44
Triruf	Oromia	92	6.76
Yetmen	Amhara	50	3.68
Total		1360	100

Source: ERHS Data & Own Computation

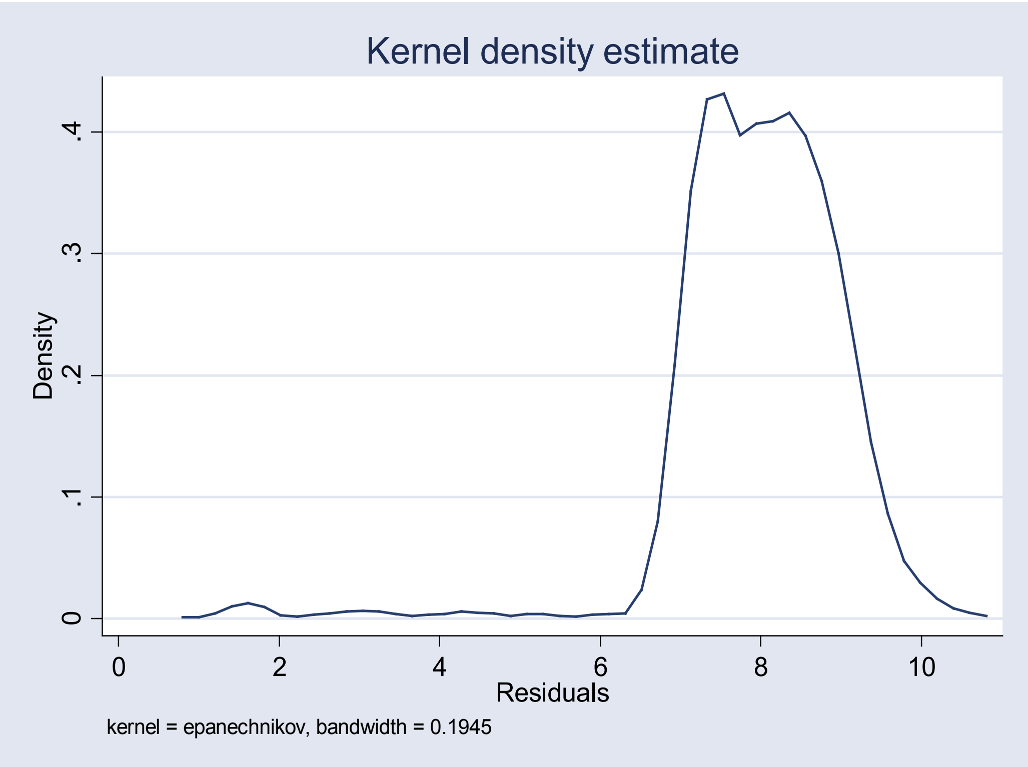
Appendix (2): MLE estimates Translog production function

	Half-Normal		Exponential		Truncated-Normal	
Variables	Coeff.	$P>\|z\|$	Coeff.	$P>\|z\|$	Coeff.	$P>\|z\|$
Constant	7.068	0.000	6.775	0.000	6.837	0.000
$\ell n(labour)$	0. 987	0.042	0.997	0.037	0.988	0.035
$\ell n(land)$	0.697	0.001	0.688	0.000	0.643	0.000
$\ell n(fertilizer)$	0.417	0.370	0.456	0.002	0.445	0.001
$\ell n(farm\ equpment)$	0.510	0.132	0.524	0.121	0.504	0.121
$\ell n(oxen)$	0.065	0.143	0.068	0.142	0.069	0.142
$\ell n(labour^2)$	0.536	0.046	0.493	0.034	0.488	0.037
$\ell n(land^2)$	-0.066	0.132	-0.015	0.129	-0.006	0.129
$\ell n(fertilizer^2)$	0.781	0.000	0.803	0.000	0.797	0.000
$\ell n(farm\ equpment^2)$	0.314	0.173	0.326	0.175	0.313	0.173
$\ell n(oxen^2)$	0.247	0.089	0.245	0.081	0.248	0.080
$\ell n(labour)*\ell n(land)$	-0.398	0.001	-0.370	0.000	-0.376	0.000
$\ell n(labour)*\ell n(fertilizer)$	0.005	0.120	0.001	0.118	0.001	0.118
$\ell n(labour)*\ell n(farm\ equp)$	0.140	0.037	0.135	0.005	0.137	0.005
$\ell n(labour)*\ell n(oxen)$	0.129	0.069	0.106	0.118	0.109	0.112
$\ell n(land)*\ell n(fertilizer)$	0.023	0.162	0.044	0.159	0.040	0.002
$\ell n(land)*\ell n(farm\ equp)$	-0.234	0.045	-0.266	0.032	-0.254	0.004
$\ell n(land)*\ell n(oxen)$	-0.303	0.023	-0.389	0.003	-0.377	0.002
$\ell n(fertilizer)*\ell n(farm\ equ)$	-0.040	0.074	-0.044	0.018	-0.043	0. 017

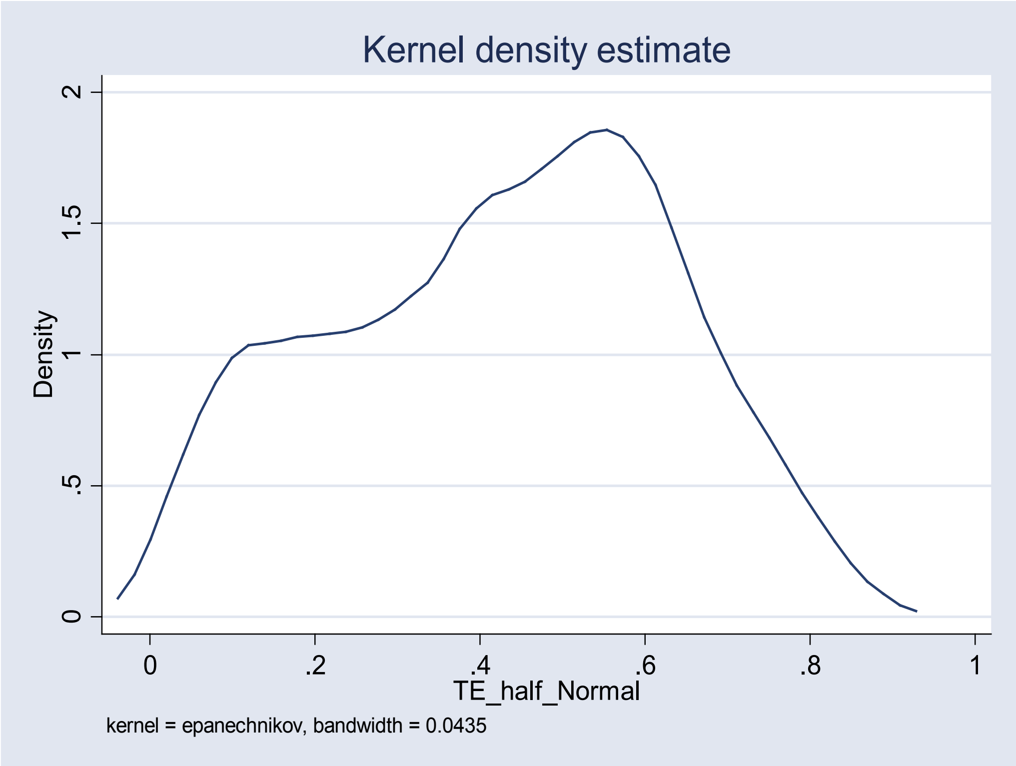
$\ell n(fertilizer) * \ell n(oxen)$	0.050	0.036	0.046	0.000	0.047	0.091
$\ell n(farm\ equ) * \ell n(oxen)$	-0.126	0.160	-0.073	0.156	-0.083	0.158
sigma_u	1.203	0.000	0.709	0.000	2.988	0.063
sigma_v	0.503	0.000	0.560	0.000	0.546	0.000
lambda	2.391	0.002	1.265	0.001	5.471	0.149
Mu	-		-		-10.50	13.51
Log-Likelihood	-1724.00		-1715.23		-1714.76	
No of Observation	1360		1360		1360	

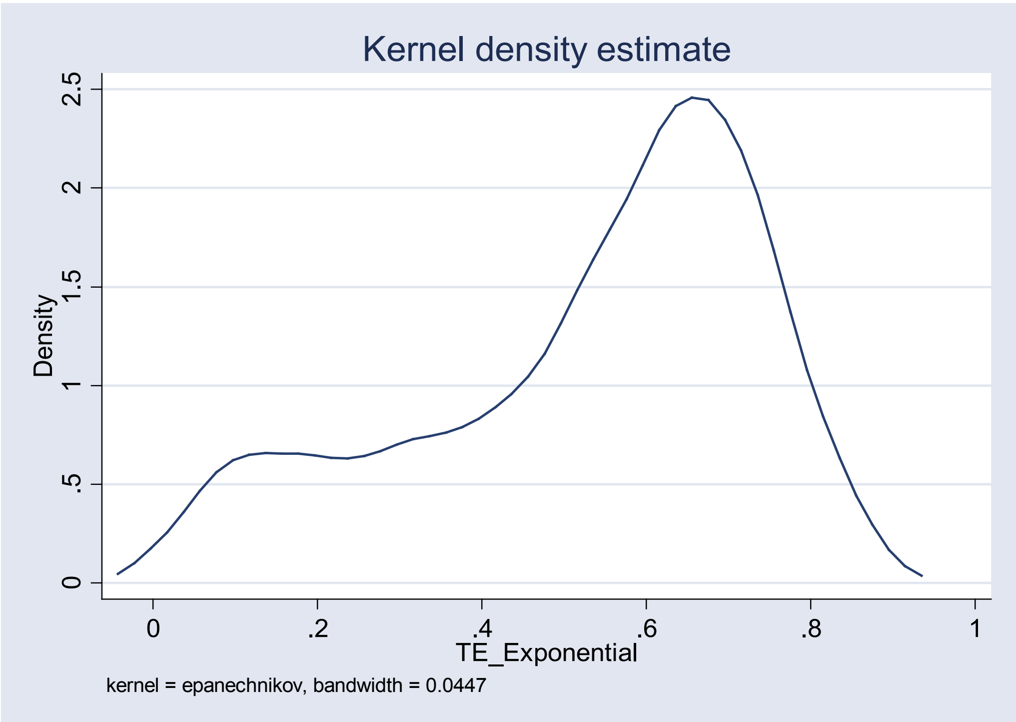
Source: Own Computation

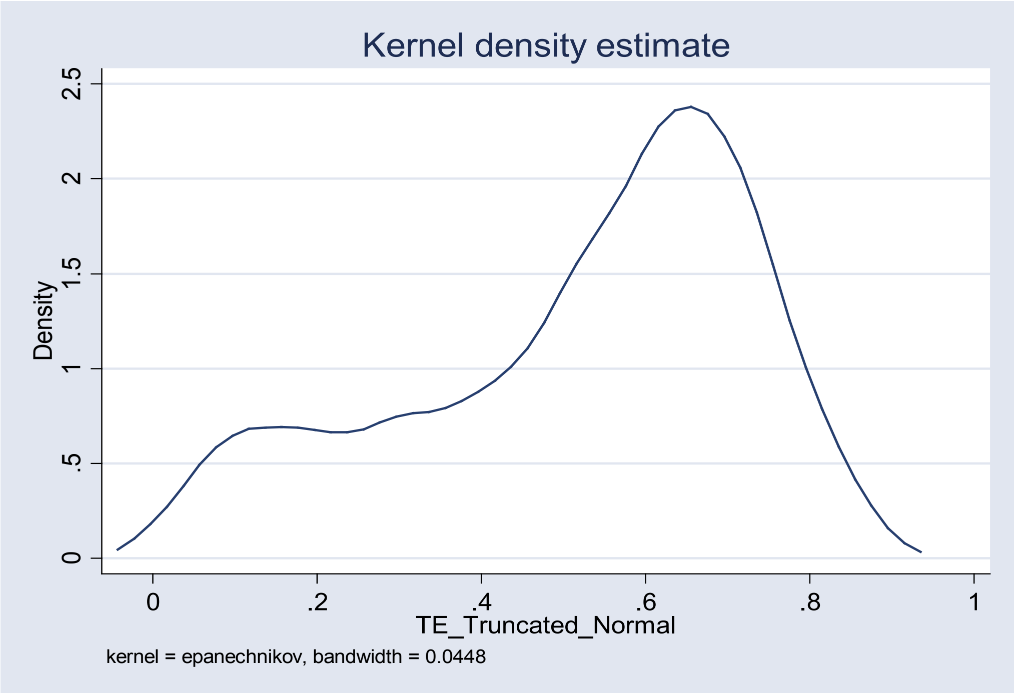
Appendix (3): Kernel density estimate of OLS residuals



Appendix (4): Kernel density estimate of Half-normal, Exponential and Truncated models







Appendix (5): Distribution and Summary of technical efficiency in the half-normal, exponential and truncated models

	Half-Normal	Exponential	Truncated-Normal
Distributions of TE Scores			
0.00-0.20	18.68	11.62	12.35
0.21-0.30	10.96	6.99	6.62
0.31-0.40	13.90	7.94	8.31
0.41-0.50	16.69	9.85	10.88
0.51-0.60	19.71	18.60	18.97
0.61-0.70	12.43	26.54	25.66
0.71-0.80	5.96	15.44	14.56
0.81-1.00	1.69	3.01	2.65
Summary of TE Scores			
Mean	0. 4271	0. 5299	0. 5208
Std.Dev.	0. 2145	0. 2108	0. 2108
Minimum	0.1094	0. 1392	0. 1392
Maximum	0.8852	0. 8904	0. 8904
Observation	1360	1360	1360

Source: Own Computation

Appendix (6): MLE estimates Production function of farm households with Off-farm income

	Half-Normal model		*Exponential model*		*Truncated-Normal model*	
Variables	*Coeff.*	*P>|z|*	*Coeff.*	*P>|z|*	*Coeff.*	*P>|z|*
Constant	*6.975*	*0.000*	*6.672*	*0.000*	*6.673*	*0.000*
$\ell n(labour)$	*0.160*	*0.032*	*0.152*	*0.039*	*0.152*	*0.042*
$\ell n(land)$	*0.805*	*0.001*	*0.978*	*0.000*	*0.978*	*0.000*
$\ell n(fertilizer)$	*0.142*	*0.000*	*0.138*	*0.000*	*0.138*	*0.000*
$\ell n(farm\ equpment)$	*0.193*	*0.001*	*0.182*	*0.023*	*0 .183*	*0.000*
$\ell n(oxen)$	*0.223*	*0.016*	*0.202*	*0.015*	*0.203*	*0.016*
sigma_u	*1.187*	*0.000*	*0.705*	*0.000*	*0.880*	*0.263*
sigma_v	*0.489*	*0.000*	*0.528*	*0.000*	*0.306*	*0.000*
lambda	*2.425*	*0.000*	*1.333*	*0.000*	*2.874*	*0.163*
Mu	*-*		*-*		*-0.461*	*0.187*
Log-Likelihood	*-871.225*		*-858.894*		*-858.906*	
Mean TE	*0.4755*		*0.5786*		*0.5783*	
No of Observation	*698*		*698*		*698*	

Source: Own Computation

Appendix (7): MLE estimates Production function of farm households without Off-farm income

Variables	*Half-Normal model*		*Exponential model*		*Truncated-Normal model*	
	Coeff.	*P>|z|*	*Coeff.*	*P>|z|*	*Coeff.*	*P>|z|*
Constant	*7.771*	*0.000*	*7.405*	*0.000*	*7.547*	*0.000*
$\ell n(labour)$	*0.055*	*0.135*	*0.046*	*0.036*	*0.049*	*0.036*
$\ell n(land)$	*0 .832*	*0.000*	*0.920*	*0.000*	*0.889*	*0.000*
$\ell n(fertilizer)$	*0.088*	*0.000*	*0.096*	*0.000*	*0.094*	*0.000*
$\ell n(farm\ equpment)$	*0.150*	*0.039*	*0.152*	*0.039*	*0.151*	*0.006*
$\ell n(oxen)$	*0.225*	*0.078*	*0.201*	*0.027*	*0.207*	*0.001*
sigma_u	*1.398*	*0.000*	*0.839*	*0.000*	*2. 509*	*0.024*
sigma_v	*0.481*	*0.000*	*0.556*	*0.000*	*0.529*	*0.000*
lambda	*2.909*	*0.000*	*1.509*	*0.000*	*4.738*	*0.000*
Mu	-		-		*-5.210*	*0.205*
Log-Likelihood	*-893.5507*		*-890.5749*		*-889.5798*	
Mean TE	*0.4105*		*0.5104*		*0.5057*	
No of Observation	*662*		*662*		*662*	

Source: Own Computation

References

Ahmed, B., Haji, J., & Geta, E. (2013). Analysis of farm households' technical efficiency in production of smallholder farmers: The case of Girawa district, Ethiopia. *American-Eurasian Journal of Agricultural & Environmental Sciences*, 13(12), 1615-1621.

Ahmed, M. H., Lemma, Z., & Endrias, G. (2014). Technical efficiency of maize producing farmers in Arsi Negelle, Central rift valley of Ethiopia: Stochastic frontier approach. *Agriculture & Forestry/Poljoprivreda i Sumarstvo*, 60(1).

Aigner, D., Lovell, C. A., amp, & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21-37.

Al-hassan, S. (2012). Technical efficiency in smallholder paddy farms in Ghana: An analysis based on different farming systems and gender. *Journal of Economics and Sustainable Development*, 3(5), 91-105.

Alemu, B. A., Nuppenau, E., & Boland, H. (2004). Technical efficiency of farming systems across agro-ecological zones in Ethiopia: An application of stochastic frontier analysis. PhD dissertation presented to Department of Environmental Management and Market research,Justus-Liebig University of Giessen, Germany.

Alene, A., & Hassan, R. (2003a). The determinants of farm-level technical efficiency among adopters of improved maize production technology in Western Ethiopia. *Agrekon*, 42(1), 1-14.

Alene, A. D. (2003). Improved production technology and efficiency of smallholder farmers in Ethiopia: Extended parametric and non-parametric approaches to production efficiency analysis. PhD Thesis, University of Pretoria, South Africa.

Alene, A. D., & Hassan, R. M. (2003b). Measuring the impact of ethiopia's new extension program on the productive efficiency of farmers. Paper presented at the Proceedings of the 25th International Conference of Agricultural Economists (IAAE).

Alene, A. D., & Zeller, M. (2005). Technology adoption and farmer efficiency in multiple crops production in Eastern Ethiopia: A comparison of parametric and non-parametric distance functions. *Agricultural Economics Review*, 6(1), 5.

Amare, H. (2005). Analysis of technical efficiency in sorghum production: The case of smallholder farmers in Raya-Azebo district, Southern Tigray, Ethiopia. An M.Sc. Thesis presented to the School of Graduate Studies of Haramaya University, Ethiopia.

Asefa, S. (2012). Who is technically efficient in crop production in Tigray region, Ethiopia? Stochastic frontier approach. *Global Advanced Research Journal of Agricultural Science*, 1(7), 191-200.

Babatunde, R. (2013). On-farm and off-farm works: Complement or substitute? Evidence from rural nigeria. Paper presented at the 4th International Conference of the African Association of Agricultural Economists, September 22-25, 2013, Hammamet, Tunisia.

Babatunde, R., Olagunju, F., Fakayode, S., & Adejobi, A. (2010). Determinants of participation in off-farm employment among small-holder farming households in Kwara state, Nigeria. *Production Agriculture and Technology*, 6(2), 1-14.

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, Dynamics, and Policy implications. *Food policy*, 26(4), 315-331.

Battese, G. E., & Coelli, T. J. (1993). A stochastic frontier production function incorporating a model for technical inefficiency effects (Vol. 69): Department of Econometrics, University of New England Armidale.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2), 325-332.

Bedemo, A., Getnet, K., Kassa, B., & Chaurasia, S. (2013). Off-farm labor supply decision of adults in rural Ethiopia: Double hurdle approach. *Journal of Agricultural Economics and Development*, 2(4), 154-165.

Besanko, D., & Braeutigam, R. R. (2005). Microeconomics. Hoboken: NJ: John Wiley & Sons.

Beyene, A. D. (2008). Determinants of off-farm participation decision of farm households in Ethiopia. *Agrekon*, 47(1), 140-161.

Binam, J. N., Gockowski, J., & Nkamleu, G. B. (2008). Technical efficiency and productivity potential of cocoa farmers in West African countries. *The Developing Economies*, 46(3), 242-263.

Bojnec, S., & Ferto, I. (2011). Impact of off-farm income on farm efficiency in Slovenia. Paper presented at the 2011 International Congress, August 30-September 2, 2011, Zurich, Switzerland.

Bravo-Ureta, B. E., & Pinheiro, A. E. (1997). Technical, economic, and allocative efficiency in peasant farming: Evidence from the Dominican Republic. *The Developing Economies*, 35(1), 48-67.

Chang, H. H., & Wen, F. I. (2011). Off-farm work, technical efficiency, and rice production risk in Taiwan. *Agricultural Economics*, 42(2), 269-278.

Chen, C.-F. (2007). Applying the stochastic frontier approach to measure hotel managerial efficiency in Taiwan. *Tourism Management*, 28(3), 696-702.

Chirwa, E. W. (2007). Sources of technical efficiency among smallholder maize farmers in Southern Malawi. AERC research paper 172. African Economic Research Consortium, 2007, Nairobi, Kenya.

Coelli, T., & Rao, D., G. Battese (1998) An introduction to efficiency and productivity analysis: Kulwar Academic Publishers, Massachusetts, USA.

Coelli, T. J. (1995). Recent developments in frontier modelling and efficiency measurement. *Australian Journal of Agricultural and Resource Economics*, 39(3), 219-245.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). An introduction to efficiency and productivity analysis: *Springer*.

Dercon, S., & Hoddinott, J. (2004). The Ethiopian rural household surveys: Introduction. International Food Policy Research Institute, Washington, DC Photocopy.

Deressa, T. T. (2007). Measuring the economic impact of climate change on Ethiopian agriculture: Ricardian approach. World Bank Policy Research Working Paper(4342).

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*. Series A (General), 253-290.

Feng, S. (2008). Land rental, off-farm employment and technical efficiency of farm households in Jiangxi province, China. *NJAS-Wageningen Journal of Life Sciences*, 55(4), 363-378.

Fita, L., Trivedi, M., Patel, A., Tassew, B., & Joshi, C. (2013). Determinants of technical efficiency of the dairy farmers in Ada'a district of Oromia state, Ethiopia. *Iranian Journal of Applied Animal Science*, 3(1), 59-65.

Gebre-Selassie, S. (2004). The roles of agriculture in the development process: Recent experiences and lessons from Ethiopia. Paper presented at the 2004 Inaugural Symposium, December 6-8, 2004, Nairobi, Kenya.

Gelaw, F. (2004). Analysis of technical efficiency of wheat production: A study in Machakel woreda. An M.Sc. Thesis presented to the School of Graduate Studies of Haramaya University, Ethiopia.

Geta, E., Bogale, A., Kassa, B., & Elias, E. (2013). Productivity and efficiency analysis of smallholder maize producers in Southern Ethiopia. *Journal of Human Ecology*, 41(1), 67-75.

Greene, W. (2005). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis*, 23(1), 7-32.

Haji, J. (2007). Production efficiency of smallholders' vegetable-dominated mixed farming system in Eastern Ethiopia: A non-parametric approach. *Journal of African Economies*, 16(1), 1-27.

Ibekwe, U., Eze, C., Onyemauwa, C., Henri-Ukoha, A., Korie, O., & Nwaiwu, I. (2010). Determinants of farm and off-farm income among farm households in South East Nigeria. *Academia Arena*, 2(10), 58-61.

Iheke, O., Nwaru, J., & Onyenweaku, C. (2013). The impact of migrant remittances on the technical efficiency of arable crop farm households in Southeastern Nigeria.Paper presented at the 4th international conference of the African Association of Agricultural Economists, September 22-25, 2013, Hammamet, Tunisia

Jara-Rojas, R., Bravo-Ureta, B. E., Moreira, V. H., & Diaz, J. (2012). Natural resource conservation and technical efficiency from small-scale farmers in Central Chile. Paper presented at the 2012 Conference, August 18-24, 2012, Foz do Iguacu, Brazil.

Jondrow, J., Knox Lovell, C., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2), 233-238.

Kebede, K., & Adenew, B. (2011). Analysis of technical efficiency: Lessons and implications for wheat producing commercial farms in Ethiopia. *Journal of Economics and Sustainable Development*, 2(8), 39-47.

Khai, H. V., & Yabe, M. (2011). Technical efficiency analysis of rice production inVietnam. *Journal of ISSAAS*, 17(1), 135-146.

Kilic, T., Carletto, C., Miluka, J., & Savastano, S. (2009). Rural nonfarm income and its impact on agriculture: Evidence from Albania. *Agricultural Economics*, 40(2), 139-160.

Kodde, D. A., & Palm, F. C. (1986). Notes and comments wald criteria for jointly testing equality and inequality. *Econometrica*, 54(5), 1243-1248.

Kuiper, M., Meijerink, G., & Eaton, D. (2007). Rural livelihoods: Interplay between farm activities, non-farm activities and the resource base Science for agriculture and rural development in low-income countries (pp. 77-95): *Springer*.

Kumbhakar, S. C., Biswas, B., & Bailey, D. (1989). A study of economic efficiency of Utah dairy farmers: A System Approach. *The Review of Economics and Statistics*, 71(4), 595-604.

Kumbhakar, S. C., & Lovell, C. K. (2003). Stochastic frontier analysis: Cambridge University Press.

Liu, Z., & Zhuang, J. (2000). Determinants of technical efficiency in post-collective Chinese agriculture: Evidence from farm-level data. *Journal of Comparative Economics*, 28(3), 545-564.

López-Feldman, A., Pfeiffer, L., & Taylor, J. (2007). Is off-farm income reforming the farm? Evidence from Mexico: Draft Paper, Department of Agricultural and Resource Economics, University of California, Davis, USA.

Msuya, E. E., Hisano, S., & Nariu, T. (2008). "Explaining productivity variation among smallholder maize farmers in Tanzania",proceedings of xii world congress of Rural Sociology of International Rural Association, Goyang, Korea.

Neumann, K., Verburg, P. H., Stehfest, E., & Müller, C. (2010). The yield gap of global grain production: A Spatial Analysis. *Agricultural Systems*, 103(5), 316-326.

Nkegbe, P. K. (2012). Technical efficiency in crop production and environmental resource management practices in Northern Ghana. *Environmental Economics*, 3(4), 43-51.

Nyagaka, D. O., Obare, G. A., Omiti, J. M., & Nguyo, W. (2010). Technical efficiency in resource use: Evidence from smallholder Irish potato farmers in Nyandarua North district, Kenya. *African Journal of Agricultural Research*, 5(11), 1179-1186.

Obwona, M. (2006). Determinants of technical efficiency differentials amongst small and medium scale farmers in Uganda: A case of tobacco growers (Vol. 152): African Economic Research Consortium, Nairobi, Kenya.

Pfeiffer, L., López-Feldman, A., & Taylor, J. E. (2009). Is off-farm income reforming the farm? Evidence from Mexico. *Agricultural Economics*, 40(2), 125-138.

Piesse, J., & Thirtle, C. (2000). A stochastic frontier approach to firm level efficiency, technological change, and productivity during the early transition in Hungary. *Journal of Comparative Economics*, 28(3), 473-501.

Rahman, M. (2007). Socio-economic determinants of off-farm activity participation in Bangladesh. *Russian Journal of Agricultural and Socio-Economic Sciences*, 1, 13.

Reardon, T., Stamoulis, K., Balisacan, A., Cruz, M., Berdegué, J., & Banks, B. (1998). Rural non-farm income in developing countries. *The state of food and agriculture*, 1998, 283-356.

Rizov, M., Gavrilescu, D., Gow, H., Mathijs, E., & Swinnen, J. F. (2001). Transition and enterprise restructuring: The development of individual farming in Romania. *World Development*, 29(7), 1257-1274.

Schmidt, P., & Knox Lovell, C. (1979). Estimating technical and allocative inefficiency relative to stochastic production and cost frontiers. *Journal of Econometrics*, 9(3), 343-366.

Singh, K., Dey, M. M., Rabbani, A. G., Sudhakaran, P. O., & Thapa, G. (2009). Technical efficiency of freshwater aquaculture and its determinants in Tripura, India. *Agricultural Economics Research Review*, 22(2), 185-119.

Solis, D., Bravo-Ureta, B. E., & Quiroga, R. E. (2007). Soil conservation and technical efficiency among hillside farmers in Central America: A Switching regression model. *Australian Journal of Agricultural and Resource Economics*, 51(4), 491-510.

Tan, S., Heerink, N., Kuyvenhoven, A., & Qu, F. (2010). Impact of land fragmentation on rice producers' technical efficiency in South-east China. *NJAS-Wageningen Journal of Life Sciences*, 57(2), 117-123.

Tirkaso, W. T. (2013). The role of agricultural commercialization for smallholders productivity and food security.An M.Sc. Thesis presented to Department of Economics,Swedish University of Agricultural Sciences,Uppsala,Sweden.

Van Keilegom, I., & Wilson, P. W. (2012). Exploring research frontiers in contemporary Statistics and Econometrics: *Springer*.

Waldman, D. M. (1982). A stationary point for the stochastic frontier likelihood. *Journal of Econometrics*, 18(2), 275-279.

Woldehanna, T. (2000). Economic analysis and policy implications of farm and off-farm employment: A case study in the Tigray region of Northern Ethiopia. Landbouwuniversiteit Wageningen (Wageningen Agricultural University), Wageningen.

Woldehanna, T. (2002). Rural farm/nonfarm income linkages in Northern Ethiopia. Promoting farm/nonfarm linkages for rural development: Case studies from Africa and Latin America, Rome: FAO, 121-144.

World Bank (2007). World development report 2008: Agriculture for development.Washington,DC: World Bank.

Yue, B., & Sonoda, D. (2012). "The effect of off-farm work on farm technical efficiency in China". Working paper, Nagoya University. Furi-cho,Chikusa-ku,Nagoya,Japan.

Zahonogo, P. (2011). Determinants of non-farm activities participation decisions of farm households in Burkina Faso. *Journal of Development and Agricultural Economics*, 3(3), 174-182.

Declaration

I hereby affirm that the present thesis with the title "***OFF-FARM INCOME AND TECHNICAL EFFICIENCY OF SMALLHOLDER FARMERS IN ETHIOPIA: A STOCHASTIC FRONTIER ANALYSIS***" was prepared by myself alone and did not involve the use of any impermissible help or of any other tools than the ones indicated. All parts of the text – including tables, maps, figures, etc. – which were taken over verbatim or analogously from other published or unpublished works have been identified accordingly. The thesis has not yet been submitted in the same or a similar form within the context of another examination, and has not been published either in part or in its entirety.

Uppsala, Sweden, 19th June 2014

Place, Date of submission

Signature