Sveriges lantbruksuniversitet
Swedish University of Agricultural Sciences

Department of Economics

Whole Farm Technical Efficiency: The case of Ethiopian Smallholders

- Time-Variant Stochastic Frontier Model

Astewale Bimr Melaku

Master´s thesis • 30 hec • Advanced level
Agricultural Economics and Management – Master's Programme
Degree thesis No 1187 • ISSN 1404-4084
Uppsala 2018

Whole Farm Technical Efficiency: The Case of Ethiopian Smallholders – Time-Variant Stochastic Frontier Model

Astewale Bimr Melaku

Supervisor: Yves Surry, Swedish University of Agricultural Sciences, Department of Economics

Examiner: Robert Hart, Swedish University of Agricultural Sciences, Department of Economics

Credits: 30 hec
Level: A2E
Course title: Independent project in Economics
Course code: EX0811
Programme/education: Agricultural Economics and Management – Master's Programme
Faculty: Faculty of Natural Resources and Agricultural Sciences

Place of publication: Uppsala
Year of publication: 2018
Name of series: Degree Project/SLU, Department of Economics
Part number: 1187
ISSN 1401-4084
Online publication: http://stud.epsilon.slu.se

Keywords: smallholder farmers, technical efficiency, time-variant, Ethiopia

Sveriges lantbruksuniversitet
Swedish University of Agricultural Sciences

Faculty of Natural Resources and Agricultural Sciences
Economics

Abstract

This study uses a time-varying random-effects stochastic frontier model to estimate level of whole farm technical efficiency using 3,465 observations of sample smallholder farmers located in Tigray, Amhara, Oromia, and Southern Nation and Nationalities (SNNP) regions of Ethiopia. A baseline econometric analysis has been done by employing Corrected Ordinary Least Square (COLS) and cross-section data models prior to the panel data model analysis as a robustness check. A panel data, composed of the three waves of the Ethiopian Socioeconomic Surveys (ESS) conducted between 2011 and 2016, is used where each smallholder farmer in the sample is observed three times. The mean of estimated level of household-specific technical efficiency is estimated to be 53 percent with individual efficiency scores ranging from 0.14 to 89 percent. This indicates that if the average smallholder farmer was to achieve the technical efficiency level of the most efficient farmer, it could be possible to realize a 40 percent (1-[0.53⁄0.89]) increment in value of output by average farmer. The study further reveals access to credit, beekeeping, crop rotation, and time-trend variables are important determinants of technical inefficiency. Thus, agricultural policies would be in a better position to achieve increased smallholder productivity by promoting these activities. Rural women empowerment and activities that minimize smallholders' vulnerability to natural shocks play a key role to boost crop and/or livestock productivity. Regional mean technical efficiency scores are significantly different from each other. Thus, it would be important to have some sort of experience or best-practice sharing platforms among regions so that smallholders in different locations have opportunities to increase their productivity up to the level of best performing farmers. The time-trend variable and estimated level of technical efficiency found to be positively correlated. This implies that lessons from actions by development initiatives in each year need to be documented, disseminated using appropriate communication tools, and scaled up to a wider range of farming community. Further studies are recommended to investigate the major location-specific causes for such huge gaps between the most technically efficient and inefficient stallholder farmers.

Acknowledgement

First and foremost, I would like to express my sincere gratitude to Swedish Institute (SI) for offering me full scholarship for the entire study period. Next, I would like to thank my supervisor, Professor Yves Surry for his academic advice and comments during the thesis work.

A very special thanks goes to Desalegne Demeke and Bete Demeke who have always been there to encourage and support me. Thank you again Bete Demeke – your comments were quite important. I would also like to express my gratitude to Dr. Belete Deribie for his continued professional advices.

My friends, Abenezer Aklilu and Wondimagegn Tafesse deserve my sincere appreciation for their suggestions and comments on my thesis.

I also want to thank the Central Statistics Agency (CSA) of Ethiopia and the World Bank's Living Standards Measurement Study (LSMS) team for freely availing the Ethiopian Socioeconomic Surveys (ESS).

Finally, my deepest gratitude goes to my family for their unconditional love and prayer.

Table of Contents

List of Figures

List of Tables

Acronyms

AGP	Agricultural growth Program
ATA	Agricultural Transformation Agency
CD	Cobb-Douglas
COLS	Corrected Ordinary Least Square
CPI	Consumer Price Index
EA	Enumeration Area
GDP	Gross Domestic Product
GLS	Generalized Least Squares
GTP I(II)	Growth and Transformation Plan I(II)
HH(H)	Household (Head)
ML(E)	Maximum-Likelihood (Estimator)
MoFED	Ethiopian Ministry of Finance and Economic Development[1].
NBE	National bank of Ethiopia
OLS	Ordinary Least Square
PASDEP	A Plan for Accelerated and Sustained Development to End Poverty
SFA	Stochastic Frontier Approach
SDPRP	Sustainable Development and Poverty Reduction Program
USAID	United States Agency for International Development
WB	World Bank
WFP	World Food Program

[1] The current Ministry of Finance and Economic Cooperation.

1. Introduction

Why smallholders? Improving smallholders' crop and livestock productivity is central not only to achieve increased yield and lead sustainable livelihood; but also contributes to poverty eradication and economic growth in such developing countries as Ethiopia. The livelihood of over 475 million smallholders, with total members of 3 billion people, is dependent on agriculture which represents 90 percent of the 570 million active farms in the world (Rapsomanikis, 2015; Abraham and Pingali, 2017). The importance of improving productivity of smallholder farming in the economic growth and poverty reduction has been recognized for years (Diao and Hazell 2004; Bahram and Chitemi 2006 and Diao *et al.*, 2007). In fact, according to Timmer and Akkus (2008), very few exceptions of countries – Singapore and Hong Kong – have been able to ensure sustained decrease in poverty without increasing agricultural productivity.

Smallholder production – which serves as a primary source of income for 81 percent of the total population of Ethiopia – dominates agricultural production of the country (WB, 2016; USAID Feed the Future, 2016). The agriculture sector remains an important contributor to overall economic growth with about 40 and 90 percent shares to the GDP and exports (including coffee and *chat*[2]) respectively (Bachewe *et al.*, 2015; and WB, 2017). The government of Ethiopia and international development partners recognized the role of smallholder agriculture as an important driver of economic development of the country (see e.g., ATA, 2018; AGP, 2018; and World Bank, 2007). As a result, the government of Ethiopia put smallholders farming at the heart of its policies. With a significant budget share to the agricultural sector, roughly seventeen percent of public expenditure, the Ethiopian development strategy supports one of the largest agricultural extension work force in the world (WB, 2016 and USAID Feed the Future, 2016).

How far to attain sustainable food security in Ethiopia? Despite rigorous works of the government of Ethiopia and development partners to improve smallholder agriculture, the rural livelihood in most parts of Ethiopia is still at its subsistence stage and highly dependent on erratic rainfalls. For example, according to Abduselam (2017), the number of people targeted as food insecure were 2.9 million in 2014, 4.5 million in mid-2015 and later at the end of the year this number grown to 10.2 million due to El Niño crisis. In late 2017, the government of Ethiopia and UN Office for the Coordination of Humanitarian Affairs (UNOCHA) identified 8.5 million people for emergency food aid (Tull, 2017). This number is in addition to eight million chronically food-insecure people who have been receiving food and cash support in the same year through the Government of Ethiopia-led Productive Safety Net Programme (PSNP)[3] (Ibid.).

So what? Haji and Andersson (2007) noted that in developing agriculture based economies, where there is lack of resources and adoption of improved technologies is limited, efficiency plays an important role in increasing productivity growth. For this reason, investigation of smallholder farmers' efficiency and hence efficiency determinants has substantial importance for economic development policy planning. According to Haji and Andersson (2007), an empirical examination of farmer's' technical efficiency helps to: i) investigate the extent to which farmers utilize the existing technology, and ii) determine the scope of possibility to increase farmers' technical efficiency without technological innovation. A wide array of applied work has been done to estimate Technical efficiency (TE) in agriculture using production frontier approach. A farmer's technical efficiency measures the farmer's ability to achieve the maximum possible agricultural output without changing the existing technology and using given set of inputs (Squires and

[2] *Chat* (Catha edulis Forsk) is a mildly narcotic, stimulant perennial crop which is produced under an intensive production system and young tender leaves and succulent twigs are chewed to gain mild excitement (Haji and Andersson, 2007 p.9).
[3] Established in 2005, PSNP is aimed at enabling the rural poor facing chronic food insecurity to resist shocks, create assets and become food self-sufficient (WFP, 2012).

Tabor, 1991). Technical efficiency of an individual farmer is measured based on his/her deviation, in terms of output, from the best-practice frontier or frontier production (Ibid.).

1.1 The Research Problem

This paper identified three gaps in the technical efficiency studies conducted in Ethiopia. First, to the researcher's knowledge, little effort has been exerted to consider livestock production in studies regarding technical efficiencies of smallholding farmers in Ethiopia. The only exception is a technical efficiency study one by Haji and Andersson (2006), which included livestock production in whole-farm efficiency analysis. The major proportion of studies on technical efficiencies done in different parts of Ethiopia exclusively focused on crop production (Croppenstedt and Demeke, 1997; Admassie, 1999; Alemu *et al.*, 2004; Alene and Zeller, 2005; Ahmed *et al.,* 2013; Tirkaso, 2013; Seyoum *et al.*, 1998; Alene and Hassan, 2003a; Geta *et al.,* 2013; Ahmed *et al.,* 2014; all focused on either single or multiple crop production efficiencies). Nevertheless, investigation of smallholders' efficiency wouldn't be free from criticism of biasedness as long as no attempt is made in considering livestock production – which is a significant contributor for rural household economy. According to CSA and WB (2013, 15 and 17); 81.6 percent, 86.5 percent, and 87 percent of households have been practicing mixed farming (crop farming and livestock rearing) among sample rural households in the 2011, 2013, and 2015 waves ESS respectively. Technical efficiency studies of specialized farms would be reliable since inputs and outputs of production frontiers would be easily identified. In case of Ethiopian smallholders, where farm inputs cannot be easily allocated between crops and livestock production, it is not easy to get data with precise inputs division to estimate separate or sub-sector frontiers.

In order to have better understanding of crop-livestock farming, this paragraph describes a hypothetical example of a typical Ethiopian smallholding farmer operating on a mixed-farming system. Suppose a farmer has a small plot of land where she/he grows few types of crops on it. Draft animal power is used for transportation, tillage, cultivation, and threshing activities associated with crop production on this farm. Those animals at the same time are parts of inputs for livestock production either in the form of livestock (by)products per annum or annual gain in weights of animals. The land is used to produce edible crops and the crop residues will be saved and used as livestock feed throughout the year. Hence, this plot of land is technically used as an input for both crop production and livestock production indirectly. Household members divide their day time for crop production activities, looking after livestock, or doing both at the same time. Traditional plough and other farm tools can be considered as a capital in producing both crops and livestock feeds. Fertilizer cost is not only input for crop production, but also it contributes for increased quantity of feed production at the same time. Similarly, veterinary expenses are incurred to improve livestock health where crop production will also be positively affected as the healthier the animal the higher animal draft power is. Hence, almost all fixed and variable inputs including cattle, fertilizer, plough, and labor are jointly utilized towards increased total production. The proportion of ratio of sub-sectors' production to the total farm output is not homogenous across smallholders.

In this scenario, no input can be considered as an exclusive input either for crop or livestock production. Depending on the weights of divisions of inputs between crop and livestock productions, keeping other factors constant, a farmer could be considered as less efficient in one of the sub-sectors while he is more technically efficient in whole-farm or other sub-sectors production. As far as smallholders' economy is concerned, conclusions and policy recommendations only based on technical efficiency of single specialization would be misleading. Therefore, it is more appropriate to consider all inputs utilized for mixed-farming operations and estimate total annual farm outputs in investigating technical efficiencies and identifying determinants of inefficiencies. Note: over nine-tenths of sample smallholder farmers included in this study are crop-livestock farmers and the remaining few have only either livestock or crop farms.

Second, majority of technical efficiency researches in Ethiopia examined the influence of farm-specific, household characteristics, and socioeconomic factors on farm efficiencies. Environmental or geo variables, however, given less attention perhaps due to data limitation. Since smallholders' agricultural production is highly dependent on environmental factors including of soil quality, topography, and climatic conditions, Sherlund *et al.* (2002) argues that environmental variables should be included in the estimation stochastic frontier. However, most technical efficiency studies fail to do so due to limited availability of data with detailed information on environmental production conditions (Sherlund *et al.*, 2002; and Ogada *et al.*, 2014). Sherlund *et al.* (2002) noted that the neglect of environmental variables leads to omitted variable bias and inaccurate estimates of technical efficiency scores. Thus, this study included agro-ecological variables in order to account for inter-farm heterogeneity in environmental production conditions such as soil quality, water, topography, and climatic conditions. Agro-ecological zonation is usually made based on agricultural and ecological features. According to Hurni (1998 p.1), each agro-ecological zone in Ethiopia has similar attributes in terms of: (i) agro-climatic conditions for crop farming and livestock rearing, (ii) land resource types such as soil, water or vegetative parameters, and (iii) topographical conditions. The map of Ethiopia with agro-ecological classification is presented in Appendix 8.1 Figure 4 (a). In addition, the farming system classification by Amede *et al.* (2017) indicates that farming systems differ from place to place mostly depending on which agro-ecological zone is the farmer located in (see Appendix 8.1 Figure 4 (b)). Thus, the inclusion of agro-ecological variable in the estimation of production frontier is assumed to capture for unobserved factors due to heterogeneity in several environmental production factors.

Third, only few technical efficiency papers appear to be done using panel data to estimate technical efficiency of Ethiopian smallholders. However, from econometric perspective, panel data is preferred to cross-section data because more accurate estimation of model parameters would be found when each individual is observed more than once (Thiam *et al.,* 2001 p.237).

1.2 Research Objectives

General Research Question:

To what extent can total agricultural output be increased among sample smallholder farmers using the existing level of technology and given set of inputs and which factors influence this increment?

Purpose:

To determine the level of technical efficiencies of smallholders' whole-farm production and examine the influence of different factors on and trends of estimated farm technical inefficiencies.

Specific objectives:

- To estimate mean technical efficiencies of crop-livestock producers among smallholder farmers located in parts of major agricultural supplier regions of Ethiopia – Tigray, Amhara, Oromia, and SNNP[4].
- To examine the patterns of estimated level of technical efficiencies across regions, across different landholding and livestock holding sizes, and over years.

[4] Southern Nation Nationalities and Peoples (SNNP) region of Ethiopia.

- To investigate the effect of different inefficiency determinants on technical inefficiency of smallholders farmers under analysis

***How*?** The present thesis utilizes stochastic frontier model in order to estimate technical efficiency of smallholders' farm production; and identify determinants of the technical inefficiencies. Specifically, a random-effects (RE) time-variant method is employed using a panel data of smallholders across four major regions of Ethiopia. Household level farm efficiencies are estimated and mean technical efficiency is generated for the whole sample. The effect of demographic characters of households, location, and socioeconomic variables on technical inefficiency is evaluated. The patterns of level of farmers' technical efficiency have been examined across different regions, different landholding and livestock holding sizes, and trends over years.

1.3 Significance of the study

This study is expected to be an important contributor for policy or intervention strategy designing by government line ministries and/or development organizations which are working to ensure improved livelihoods among smallholders in different parts of Ethiopia**.** As the study is focused at analyzing whole-farm technical efficiency of smallholders, it will be more representative to the household economy as compared to efficiency studies focused at sub-sector of farm economy.

1.4 Organization of the Study

The rest of the thesis is organized as follows. Chapter two discusses the literature review. Chapter three presents important conceptual backgrounds to the econometric models. Chapter four explores methodology of the research in detail. Empirical results are discussed in Chapter five, while brief concluding remarks and policy recommendations are made in the last section. Finally, appendices and reference list are presented at the end consecutively.

2. Literature review

The literature review section starts with the bigger picture of agriculture and analyses the two major contradicting opinions about the importance of agricultural productivity to sustainable economic development. Then, the role of smallholder agriculture is also analyzed in detail to have basic understanding about its significance to economic growth. Some selected papers on technical efficiencies of Ethiopian smallholder farmers are examined to get opportunities to make contributions to the literature by identifying gaps. Finally, different methods of panel data approach have been highlighted in order to grasp hints about the appropriate model among several options. It is important to note that comparison of specific results of this thesis and similar studies has been done in the results section, hence comparisons of specific findings are not included in this chapter in order to avoid repetition

2.1 Agricultural productivity and economic growth – different views

There has been opposing views on the role of agriculture productivity and consequent policy suggestions towards economic development. Dethier and Effenberger (2012) clearly noted that; i) agriculture has been a major preoccupation of international development organizations and governments of developing countries during the 1960s and 1970s; ii) later, in the 1980s and 1990s, agriculture has no more been a priority on development agenda; and iii) finally, agriculture reappeared in beginning of twenty-first century because of neglect and underinvestment.

Valdés and Foster (2010) concluded that most development literature in the mid-twenties is now considered as pessimistic in terms of the potential of agriculture for productivity and export growth. In the same vein, according to Hirschman (1958), most of development papers produced during that time demonstrated opinions that agriculture was not responsive to incentives and there were weak linkages with other sectors. In recent times as well, for example, Dercon (2009) argued that less attention should be given to agriculture and rather more efforts should be exerted in importing food and strengthening other sectors in order to ensure development (Dethier and Effenberger, 2012). Due to this set of misperceptions, agriculture has been neglected in search for policies that would boost economic development. For example, the share of agriculture in official development assistance (ODA) declined sharply from the maximum of eighteen percent in 1979 to 3.5 in 2004 (World Bank, 2007).

On the other hand, following Schultz (1964), development economists have been motivated in reconsidering efficiency of farmers and potential of the sector for sustainable economic growth (Valdés and Foster, 2010 p.1364). These studies indicated agriculture is sensitive to incentives and agriculture also has greater multiplier effect than it was perceived. Recognizing convincing successes in development, the 2008 World Development Report clearly marked that agriculture has not been used to its full potential in many countries because of anti-agriculture policy biases and underinvestment (see World Bank, 2007 p.44). Consequently, in recent years, developed countries and international development agencies have renewed their interest to make huge investment in agriculture (Dethier and Effenberger, 2012; and World Bank, 2007). For example, the Group of Eight (G8)[5] countries promised to allocate 22 billion dollars for agricultural development during their meeting in Aquila, Italy in 2009 (Dethier and Effenberger, 2012).

Despite these varied narrations, opposing views regarding the role of agriculture to economic development do not necessarily contradict each other. The main reason for these differences is that development models have been derived under different economic assumptions (Dethier and Effenberger, 2012). Depending on

[5] France, Germany, Italy, Japan, the United Kingdom, and the United States, Canada, and Russia were members of the G8 (see Bayne, 2017).

the economic setup that a country has (e.g., openness to trade and being landlocked or not) and the position of agriculture in a country's economy, the role of agriculture to development will have a different outlook among countries and thus different country-specific policies need to be developed. Mellor and Johnston (1961) underscored policies should take account of the phases of agricultural development and its implication. Similarly, Heady *et al.* (1965) stressed adjustments should be made to agriculture and be consistent with the stage of economic development. Agro-pessimists also admit that agriculture can significantly contribute to economic development under certain circumstances (Dethier and Effenberger, 2012). For example, they mentioned that agriculture should be supported to stimulate overall economic growth if a country is landlocked and has a closed economy model. Hence, "tailor-made" or country- and case-specific development programs are needed to make sure that agriculture is in a better position for long-run economic benefits.

Now let us narrow the issue down to the case of smallholders who virtually represent agriculture in developing countries. Approximately 90 percent of the 570 million farms in the world are operated by 475 million farm households with a total member of three billion people (Rapsomanikis, 2015; Abraham and Pingali, 2017). In the case of developing countries, agricultural growth in comparison to the non-agricultural growth will favor the poorest in terms of increase in income – meaning better in reducing income inequalities (Valdés and Foster, 2010). On the other hand, according to Collier and Dercon (2014), it has been argued that growth in the agricultural sector is dependent on the demand which is driven by the non-agricultural parts of the economy. However, for certain landlocked economies in Africa with difficult relations with their neighbors, such as Ethiopia, it is reasonable to assume agricultural production will have to lead the growth process (Ibid.). For example, a cross-country panel data analysis by Bravo-Ortega and Lederman (2005) indicated that increase in agricultural income raises nonagricultural GDP in developing countries, while the reverse relation exists for developed countries (Dethier and Effenberger, 2012). Regarding poverty, evidence show agricultural growth in developing countries has relatively greater importance in poverty reduction than other sectors (e.g., World Bank, 2007).

2.2 Empirical Evidence on Smallholder Farmers' Technical Efficiencies in Ethiopia

Beyond ensuring a sustainable food supply, investigation of smallholders' farm efficiency and hence efficiency determinants are of substantial policy relevance for economic development. Haji and Andersson (2006) and Sherlund *et al.* (2002) noted in developing agriculture-based economies, where there is lack of resources and the adoption of improved technologies is limited, efficiency improvements play a significant role in achieving economic growth. Thus, precise estimation of efficiency scores and analysis of inefficiency determinants is quite important for public investments focused at increasing farmers' productivity (Sherlund *et al.*, 2002).

Table 1 (see Appendix 8.2) presents a brief description of some selected papers focusing on investigating technical efficiency of smallholder farmers in different parts of Ethiopia. As indicated, a total of sixteen papers are included in the list out of which ten studies are done on multiple crop production, three on maize production, two on dairy farms, and only one study has been conducted on whole farm efficiency. As shown in Table 1 (Appendix 8.2), most of the papers employed stochastic frontier approach (SFA) using cross-sectional (twelve papers). Only one paper is presented for each of the following models – data envelopment analysis (DEA), DEA and SFA with cross-sectional data, DEA and parametric distance function (PDF), and mixed fixed-random coefficients approach.

In general, a major subset of technical efficiency studies done for the last two decades in Ethiopia are mainly focused on either multiple crop production or a single crop production technical efficiency. For example, Croppenstedt and Demeke (1997), Admassie (1999), Alemu *et al.* (2004), Alene and Zeller (2005), Ahmed *et al.* (2013), and Tirkaso (2013) studied technical efficiency of multiple crop production and associated inefficiency determinants. Seyoum *et al.* (1998), Alene and Hassan (2003a), Geta *et al.* (2013), and Ahmed *et al.* (2014) examined technical efficiency of maize production and its determinants. Fita *et al.* (2013) estimated technical efficiency scores of dairy production. Likewise, Haji and Anderson (2007) studied technical efficiency of whole-farm and vegetable production and determinants of inefficiencies. Relatively, limited efforts were exerted to study technical efficiencies of farms specializing in livestock and dairy and those viewed as a whole (i.e. mixed farms).

It seems almost no one considered livestock production in studies regarding technical efficiencies of smallholding farmers in Ethiopia. The only exception to this is a research done by Haji and Andersson (2006) estimated vegetable as well as whole-farm (both crop and livestock production) efficiency in two districts. Similarly, apart from Ethiopia, the proportion of studies done globally on multiple or single crop production and dairy farm efficiencies is significantly higher than that of studies done on whole-farm efficiency. Technical efficiency studies done on cattle or livestock farming are somewhat sparse. For example, out of 167 published papers included in a meta-regression analysis done by Bravo-Ureta *et al.* (2007), only one study was done on livestock technical efficiency following the second least category – other animals (six). In the aforementioned meta-regression analysis, crops (either multiple or single crop) is the dominant category with 109 studies, followed by dairy and cattle (46), and whole farm (23). In countries like Ethiopia, the role of livestock in the economy is quite significant and hence technical efficiency study in the livestock sector would be equally important.

In mixed crop-livestock system, livestock is the second major source of household income (FAO, 2018). Likewise, at national level, the mixed crop-livestock systems contribute to a significant share, two-thirds, to the total net income (Ibid.). The crop-livestock system is concentrated in the mid- and high-altitude, where the major agricultural production comes from. As crop-livestock systems are technically very interlinked, one can hardly separate production inputs for each activity. In this case, it would be very difficult to get accurate estimates of technical efficiency and analysis of corresponding determinants if we consider sub-sector efficiency analysis of farms. The problem with input allocation, especially when one deals with national or regional level data, is that utilized multiple inputs cannot be easily broken down into crop and livestock sectors (Alene *et al.*, 2006. p.53). Due to this problem, studies conducted in sub-sector productivity – such as Rae and Hertel (2000) – were based on highly imperfect, partial factor productivity measures (Alene *et al.*, 2006. p.53). For this reason, instead of sub-sector efficiency analysis, the best alternative would be to utilize a single production frontier approach using aggregated value of all farm outputs by considering all agricultural inputs utilized.

The challenge of quantifying the annual value of production gained from livestock would be the main reason for not considering livestock production in smallholders' technical efficiency studies in Ethiopia. Likewise, estimating the amount or value of livestock feed utilized during the year is not as easy as those of the commercial farms. Commercial farms usually have records of the cost or quantity of livestock feed utilized whereas smallholders commonly use crop residues and/or free grazing to feed their livestock. Bagi and Huang (1983) estimated production technical efficiency of farms including 115 crop farms and 78 mixed-farms. In the case of mixed-farms, in addition to total value of crop output, they included the "value added" to livestock over the year and the income from actual livestock sales during the year in calculating the total output. Likewise, while calculating total mixed-farm outputs, this thesis included; i) the monetary value of crop outputs, and ii) income from actual sales of live animals, iii) income from sales of livestock products and livestock byproducts if any. Due to data limitation, the value of annual increase in herd size is not included in calculation of annual total farm outputs. Nonetheless, herd size among Ethiopian smallholders is strongly and positively associated with household's choice of participation on cattle market as a seller (Negassa and Jabbar, 2008). They also noted that for farm households in the predominantly crop–livestock systems, livestock births account the majority of inflows to the livestock herds and flocks. Similarly, livestock sale represents the major share of outflows from the livestock herd and flocks. Meaning, households with larger herd size have higher ability to generate surplus animals and are therefore more likely to sell live animals. Though the total number of livestock in Ethiopia is the largest in Africa, the number of livestock at the level of the individual smallholder farmers and remains very low (SA *et al.*, 2012).This implies that smallholders tend to keep more or less equivalent herd or flock sizes or at least no significant changes be made within a year. Hence, the value of increase in herd side can significantly be captured by the sale of live animals. For this reason, this study does not include the increase in herd size in calculating the total value of annual agricultural output.

Another dimension this thesis tries to take advantage of it is that most studies on technical efficiencies done in Ethiopia did not account for agro-ecological factors, probably due to unavailability of data. None of the papers listed in Table 1 (Appendix 8.2) included environmental or agro-ecological production conditions. Ignoring such factors cost a lot in terms biased parameter estimation and variations due to these factors will be regarded as real efficiency differences (see e.g., Ogada *et al.*, 2014; and Liu and Zhuang, 2000). Salami *et al.* (2010) showed smallholders can be categorized on the basis of the agro-ecological zones in which they operate for more precise policy designing and implementation. Thus, for accurate results, this thesis incorporated agro-ecological zones (as dummy variables) in order to account for uncontrolled location-specific climate factors.

2.3 Panel Data Models in Technical Efficiency Studies

Based on the data type they use, econometric estimation of stochastic production frontiers can be categorized as cross-section or panel data models. Model (4) is a stochastic frontier production function defined for cross-sectional data where each household is observed once at a particular time. If households (farmers) in the sample are observed at several times over time, then the data are referred to as panel data. Schmidt and Sickles (1984) pointed out major limitations associated cross-section studies: i) inconsistent estimates of a particular firm technical (in)efficiency; ii) estimation of the model and separation of the inefficiency from the statistical noise requires specific distributional assumption (e.g., half-normal or exponential); iii) it may not be correct to assume that inefficiency is independent of regressors. Panel data model solves all these problems because one can take into account some heterogeneity and some rigidities or limitations can be removed (Schmidt and Sickles, 1984; Thiam *et al.,* 2001; Murillo-Zamorano, 2004; and Battese and Coelli, 1995). Moreover, from an econometric perspective, panel data is preferred to cross-section data because more accurate estimation of model parameters would be found when each individual is observed more than once (Thiam *et al.,* 2001, p.237).

Nevertheless, a significant share of farm technical efficiency studies in Ethiopia employed cross-section data probably due to data limitations (e.g., Abebe, 2014; Ahmed *et al.,* 2013; Tirkaso, 2013; Asefa, S., 2011; Wubeneh and Ehui, 2006; Alene *et al.*, 2006; Haji and Andersson, 2006; and Seyoum *et al.*,1998). There are few exceptions which used panel data analysis (e.g., Demeke *et al.*, 2011). Understandably, one of the gaps this thesis is supposed to fill is that most technical efficiency studies in Ethiopia do not utilize panel data.

3. Conceptual background

This section explains the conceptual models used for analyses and alternative models which are not considered in this study. The discussion starts with the wider concept, economic efficiency, where basic economic background to technical and allocative efficiency is provided. Several production frontier approaches are also discussed and justification for selecting stochastic frontier approach is provided. Moreover, the specific model selected for this study, time-variant random effects model, is explained in detail and its advantage over other alternative methods is also provided.

3.1 Economic efficiency and its components

In his well-known paper, Farrell (1957) categorized efficiency of a firm into two components: *technical efficiency* – the ability of a firm to obtain the maximum attainable output available from a determined set of inputs, and *allocative efficiency* – the ability of a firm to use optimal package of inputs given their prices and marginal productivities. Economic efficiency, therefore, can be defined as a well-specified output at minimum cost[6]. Two important questions could arise in relation to economic efficiency: (*i*) "to what amount can factor inputs proportionally be reduced without affecting a given level of output?" and (*ii*) to what extent can output level be proportionally expanded without altering a given set of inputs?" Farrell addressed these two questions through input-oriented and output-oriented efficiency measures respectively.

For a better understanding of economic or overall efficiency and its components, Farrell's analysis of output-oriented measures of efficiency was illustrated by Coelli (1996) as shown in Figure 1. Consider a case where production involves two outputs (Y_1 and Y_2) and a single input X.

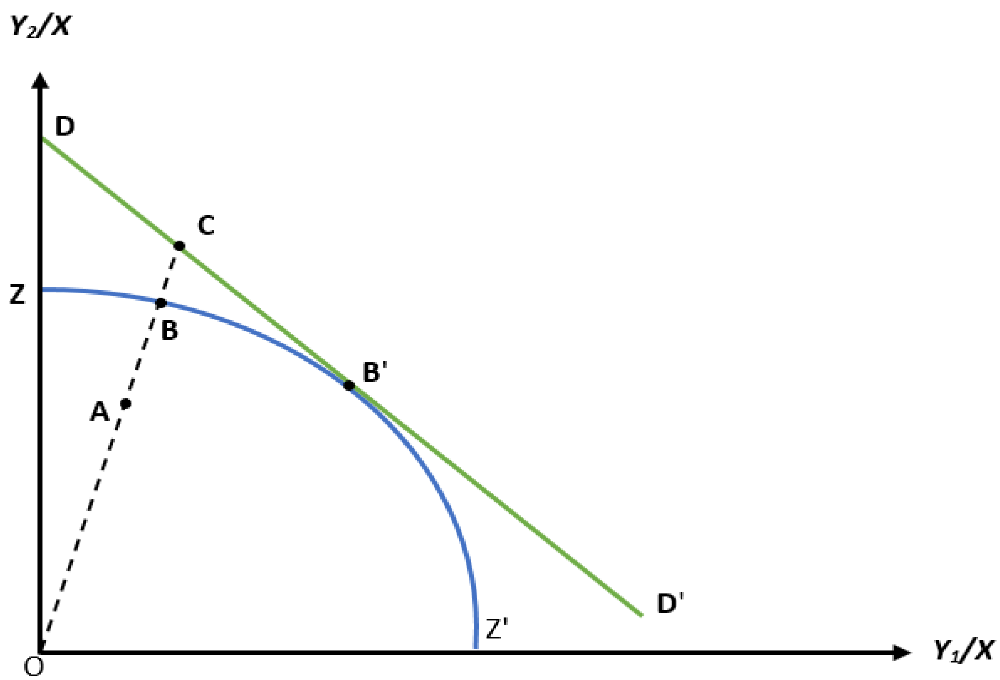


Figure 1. Technical and allocative Efficiency from an output orientation. (Source: Coelli, 1996).

[6] Farrell (1957) termed *price efficiency* and *overall efficiency* instead of latter literature terminologies of *allocative efficiency* and *economic efficiency* respectively (*Coelli, 1996*).

For simplicity, one can assume constant returns to scale (CRS) therefore technology can be represented by a unit production possibility curve XX' in two dimensions. The curve ZZ' is the unit production possibility curve, i.e. it represents the upper bound of production possibilities. Such firms operating below the ZZ' curve as the one which operates at point A are therefore inefficient. Hence, the distance AB along the ray OC' represents technical inefficiency of a firm operating at point A, meaning output could be increased without requiring additional input. Geometrically, technical inefficiency of the firm operating at point A can be expressed by the ratio AB/OB. Hence, the technical efficiency (TE) of the firm under analysis (1-AB)/OB would be given by the ration of OA/OB.

Assuming market price is given and a particular behavioral objective such as revenue maximization is assumed in such a way that the output price ratio is reflected by the slope of isorevenue line DD'; allocative efficiency of the firm under study can also be derived from the unit isoresource plotted in Figure 1. Hence, the focus will now be on the distance given by the line segment BC along the array OC, which in relative terms could be given as BC/OC. The maximum attainable revenue with the given level of input is given by point B'. Therefore, the ratio BC/OC indicates that the revenue expansion that a firm would be able to achieve if it moved from a technically efficient output combination (point B) to a both technically and allocatively efficient one (point B'). This indicates that the allocative efficiency of a firm operating at point A is given by OB/OC.

The measure of what Farrell (1957) termed *overall efficiency* and later literature has renamed *economic efficiency* (EE) can be derived from the multiplicative interaction of both technical and allocative components;

$$\boldsymbol{TE} = \frac{OA}{OB} \qquad and \qquad \boldsymbol{AE} = \frac{OB}{OC} \tag{1}$$

$$\boldsymbol{EE} = TE \times AE = \frac{OA}{OB} \times \frac{OB}{OC} = \frac{\boldsymbol{OA}}{\boldsymbol{OC}} \tag{2}$$

where the distance involved in its definition (AC) can also be analyzed in terms of revenue expansion.

The output-oriented efficiency analysis of Farrell (1957) is described in this section in order to have better understanding about economic efficiency and its components – technical and allocative efficiency. A thorough analysis of input-oriented efficiency measures can be found in Murillo-Zamorano (2004) and Coelli (1996). It is worth to mention here that under the assumption of CRS, input-oriented and output-oriented measures of technical efficiency are equivalent (Färe and Lovell, 1978).

3.2 Production frontier approaches

In microeconomic theory a production function (or *frontier*) is defined in terms of the maximum output that can be produced from a determined package of inputs given the existing technology. A large number of frontier models developed based on Farrell's original work in 1957 can be classified into two major categories – *parametric* and *non-parametric* (Thiam *et al.*, 2001). Non-parametric TE models, often referred to as Data Envelopment Analysis (DEA), are based on mathematical programing techniques. Unlike the parametric models, DEA neither imposes any functional form nor makes assumptions about the error terms. Though DEA is free from misspecification, it is not preferred for analysis in this thesis due mainly to its failure to account for measurement errors and other sources of statistical noise. Thus, as all deviations from the frontier are assumed to be the resulted from technical inefficiency, real efficiency scores may be under estimated (Hansson Öhlmér, 2008).

Parametric models can either be non-stochastic or stochastic. As Murillo-Zamorano (2004) explained, the non-stochastic econometric approach enables analysts to estimate rather than 'calculate' the parameters of the function by adopting the technological framework introduced in the mathematical programming model, i.e. statistical inference will be possible based on those estimates. Nevertheless, alike to DEA, a problem with non-stochastic frontiers is that no account is taken of statistical noise, and hence any deviation from the frontier is assumed to be caused by inefficiency.

Due mainly to their failure to provide accurate measures of productive structure (Murillo-Zamorano, 2004), goal programming models or non-stochastic econometric approaches are not used in this study. In the next section, a detailed analysis of an alternative econometric approach, *stochastic frontier models*, is provided.

3.3 Stochastic Frontier Models

As noted by Murillo-Zamorano (2004), an obvious solution to the problem associated with non-parametric and non-stochastic frontier approaches is to introduce a double-sided random error into the frontier model specification. The resulting frontier is known as stochastic frontier – where both specification failures and uncontrollable factors are modeled independently of the inefficiency component. Stochastic frontier model was independently developed by Aigner, Lovell and Schmidt (1977), and Meeusen and Van den Broeck (1977), and it can be written as:

$$Y_i = f(x_i;\ \beta)\ \exp(v_i - u_i) \qquad\qquad i = 1, 2, \dots, N \qquad\qquad (3)$$

where Y_i represents the total possible maximum output of the i^{th} firm (farmer), x_i a vector of N (farm) inputs, $f(x_i;\ \beta)$ is a suitable production frontier (it can take Cobb-Douglas or TRANSLOG functional form) which depends on inputs and a vector of technological parameter β. The term $v_i - u_i$ can be decomposed into v_i – which represents statistical noise (the regular error term) and u_i – which represents technical inefficiency, meaning the deviation of output from the frontier for each individual firm (farm). The output-oriented measure of technical efficiency of a firm can be defined as the ratio of its observed output, Y_i, to the stochastic to the corresponding stochastic output:

$$TE_i = \frac{Y_i}{f(x_i;\beta)\ \exp(v_i)} = \frac{f(x_i;\beta)\ exp(v_i - u_i)}{f(x_i;\beta)\ exp(v_i)} = exp(-u_i) \qquad\qquad (4)$$

Technical efficiency of the i^{th} firm, TE_i, takes a value between zero and one and it will be predicted once the parameters of the stochastic frontier (i.e. model (4)) are estimated. The statistical noise, v_i, is assumed to be identically independent and identically distributed. For the one-sided error (inefficiency), u_i, half-normal, exponential, exponential, and truncated-normal distributional assumptions have been frequently assumed used in the literature[7]. Under the assumption that the two error terms are independently distributed from each other and from the regressors, Maximum Likelihood estimates can be determined. A brief description of Maximum Likelihood Estimator (MLE) is provided in Appendix 8.3.

3.4 Time-Variant Model

Stochastic frontier panel data models can be either time-variant or time-invariant, mainly depending on their assumption about inefficiency over time[8]. The time-variant model assumes that inefficiency effects are firm-specific and time-varying. In the time-invariant model, inefficiency term is assumed to be firm-specific and

---

[7] A detail review of the half-normal, exponential, gamma, and truncated-normal distributional assumptions can be found in Murillo-Zamorano (2004).

[8] Multiple practical examples of time-variant and time-invariant models can be found in Kumbhakar *et al.* (2015).

time-invariant. As the time period of panel data becomes large, it is not realistic to assume that inefficiency level of a given firm does not change over time (Coelli, 1995). Kumbhakar *et al.* (2015) and Coelli (1995) suggested that time-invariant model can be employed for short time panel data models, where inefficiency determinants are not expected to change during time period of the study (Kumbhakar *et al.*, 2015; Coelli, 1995). However, based on the summary statistics of important variables from the data employed in this thesis, there are noticeable changes in output per specific inputs over years, which implies that productivity is changing over years whatever the magnitude of the change is. In fact, reports from development programs or agencies show that smallholders' productivity has been increasing over years (see e.g., ATA, 2018; AGP, 2018, World Bank, 2017). This indicates smallholders productivity growth, and hence efficiency, are expected to be improved during the period the data was collected. For this specific study, the time-variant model is well justified as at least very small difference is expected in level technical efficiency of smallholder farms over years.

Based on model (4), panel data model (i.e. Cobb-Douglas Production function) can be can be presented as follows,

$$y_{it} = \alpha + x_{it}'\beta + v_{it} - u_{it} \qquad i = 1, \dots, N, t = 1, \dots, T. \qquad (5)$$

Here, the subscripts i and t index the farm households and time periods respectively. y_{it} represents the total output of the i^{th} farm household at time t, whereas x_{it} is a vector of farm inputs utilized by the i^{th} farm household at time t. The v_{it} is statistical noise and uncorrelated with regressors. The u_{it} is technical inefficiency of the i^{th} farm household at time t, and correspondingly, $u_{it} \geq 0$ for all i.

Based on the time-variant model, one can assume u_i as a fixed – fixed-effects model or random parameter – random-effects model. Since these models do not impose any distributional assumption on u_i, they are referred as distribution-free approaches. The Fixed effects model assumes that u_i is allowed to be freely correlated with the regressors, which is may be a desirable property (Kumbhakar *et al.*, 2015). However, this models have a limitation that time-invariant attributes of the households could cause multicollinearity problem. Kokkinou (2010) also noted that fixed-effects model could provide unrealistic technical efficiency scores due to poor estimation of parameters of frontier production. Thus, the random effects model is selected for this study because the time-invariant variables, such as gender, region, and agro-ecological zones can be included as regressors without the problem of perfect multicollinearity.

The random-effects model can be estimated either by generalized least squares (GLS) or using the maximum likelihood (ML) method (see e.g., Kumbhakar *et al.*, 2015; and Schmidt and Sickles, 1984). Schmidt and Sickles (1984) noted that, as $N \to \infty$ regardless of T, MLE's are consistent and asymptotically efficient than the GLS estimator. Using ML estimator, it is possible to impose distributional assumptions on the error terms and their independence on the regressors (Schmidt and Sickles, 1984). A brief discussion of MLE and corresponding mathematical derivations are presented in Appendix 8.3.

4. Data

4.1 Smallholder agriculture in Ethiopia

Ethiopia, Africa's second most populous country, has achieved substantial economic development over the past decade envisioning to be a middle income country by 2025 (WB, 2017)[9]. The country has a population of 97 million people and a land size of 1.14 million square kilometers (WFP, 2018 and NBE, 2017). Agriculture, virtually represented by smallholders farming, has been a major pillar of the economy and remained to be the primary focus of development agendas towards the country's vision of becoming a middle income country (WB, 2016; USAID Feed the Future, 2016). The sector remains an important contributor to overall economic growth with about 40 percent and over 90 percent shares to the GDP and exports (including coffee and *chat*[10]), respectively (Bachewe *et al.*, 2015; WB, 2017).

Cereals, pulses and oilseeds altogether categorized as grain crops, constitute the major food crops for the majority of the country's population and also contribute significantly to the household income as well as foreign currency earnings (CSA, 2017). According to CSA (2017)'s main production season post-harvest crop production survey, a total of 12,574,107.33 hectares of land were covered by grain crops with a corresponding total grain yield amounting 290,385,593.21 quintals. Ethiopia has the largest livestock population and the highest draft animal population in the continent (Solomon *et al.,* 2013 p.2). There are approximately 59.5 million cattle, 60.9 million sheep and goats, 11 million equines (including horses, mules and donkeys), 59.5 poultry, 2.4 million camels and 6.2 million beehives (CSA, 2017).

The government of Ethiopia and international development partners recognized the role of smallholder agriculture as an important driver of economic development of the country (see e.g., ATA, 2018; AGP, 2018; and World Bank, 2007). The agricultural sector exhibited 6.7 percent growth rate in 2016/17, becoming the major source of the 10.9 percent GDP growth rate in the same year (NBE, 2017). The Ethiopian government, in its Growth and Transformation Plan (GTP), and the World Bank, in its Country Partnership Framework for Ethiopia, clearly stated that sustainable economic growth will be attained through smallholders' productivity (MoFED, 2014; and World Bank, 2017). Ethiopian government – in collaboration with international development organizations – has been implementing long-term country-led programs aiming at increasing production and productivity of smallholder production (WB, 2016; USAID Feed the Future, 2016). For example, Sustainable Development and Poverty Reduction Program (SDPRP)[11], Plan for Accelerated and Sustained Development to End Poverty (PASDEP)[12], and Growth and Transformation Plan I (GTP I) have been successively implemented from 2003 through 2015 (MoFED, 2002, 2006, and 2014). Smallholding agriculture was the top priority in all of these national level economic strategies. Growth and Transformation Plan II (GTP II)[13], a continuation of GTP I, is currently (2016 - 2020) under implementation with the notion that agriculture will remain key driver of economic growth (World Bank, 2017).

---

[9] Report No. 115135-ET.

[10] *Chat* (Catha edulis Forsk) is a mildly narcotic, stimulant perennial crop which is produced under an intensive production system and young tender leaves and succulent twigs are chewed to gain mild excitement (Haji and Andersson, 2007 p.9).

[11] SDPRP, a three years national level development strategy (2003 – 2005), had the following major focus areas: overriding primacy to smallholders' development, private sector growth and encourage investment, increased commodity export mainly agricultural products, investment on education, strengthen administrative decentralization, governance improvements, promoting agricultural research, and increased water resources utilization (see MoFED, 2002).

[12] PASDEP has been implemented for five years (2006 – 2010) with the following eight major pillar: capacity building, massive push towards speeding up growth mainly by greater commercialization of agriculture, balancing economic development with population growth, women empowerment, infrastructure development, development of human resource, able to manage risk and volatility, and reducing unemployment (see MoFED, 2006).

[13] GTP II intends a 20 percent increase in agricultural output by smallholders' living in the rural areas and ensure sustainable food supply to the urban people (World Bank, 2017).

4.2 Data Source and Data Processing

The Ethiopian Socioeconomic Surveys (ESS)

This thesis utilized a panel data created using the ESS, which were implemented by the Central Statistics (CSA) of Ethiopia and the World Bank's Living Standards Measurement Study (LSMS) team. According to (CSA and WB, 2013, 15, 17), ESS has been implemented in three rounds – in 2011, 2013 and 2015. The surveys were done in representative rural and small town areas of Ethiopia on a range of household community level characteristics linked to agricultural activities. The same households, with a rich set of information on agriculture, food security, shocks, demography, education, health, savings, labor, and welfare, are observed over three years. Data from all the three waves is freely availed by World Bank[14].

Data Processing

The data processing (data cleaning) was tricky and took considerable time before proceeding with the econometric analysis. The reason for this stems from the fact that the ESS data covers a wide range of topics and includes multiple data sets (over 200 data files). Hence, one has to go through several data sets to get relevant information in order to create a database of sampled farms from the ESS with all relevant variables. In addition, there is no common identifier across all data sets which makes the creation of a single data set more difficult. A thorough processing of the data which involved multiple stages of tasks, has been done to produce three cross-sectional data sets where each of them were sorted by *household id*[15]. As illustrated in figure 2, a balanced panel data consisting of 3,465 observations (1155 households) is created with a time series of three years. The data processing work as well as the analysis part is done using STATA program.

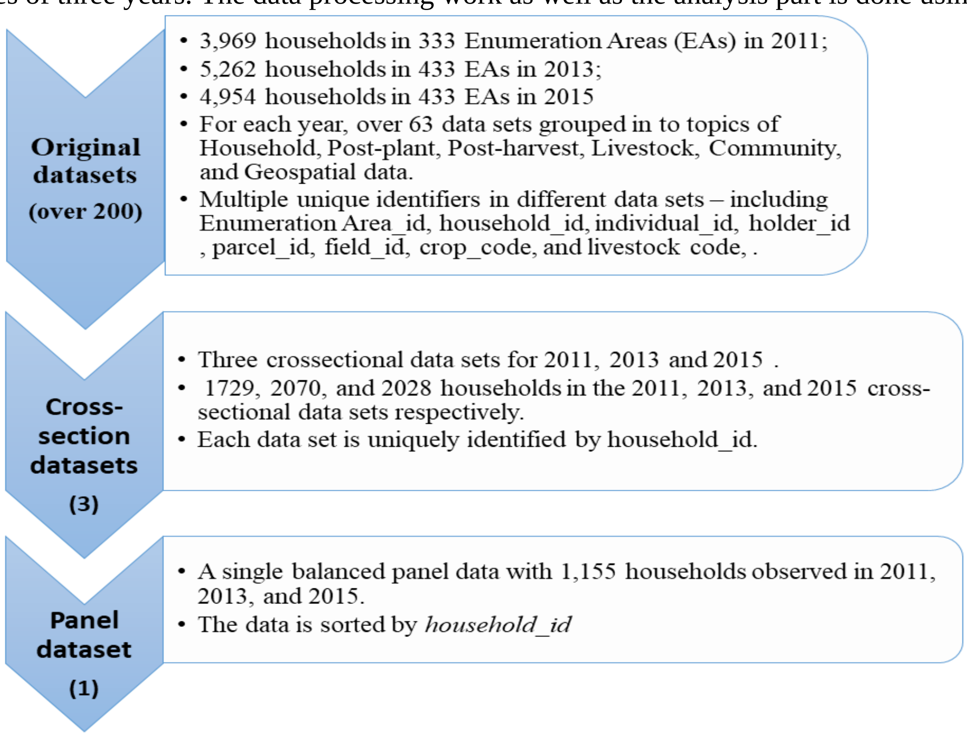


Figure 2. Dataset creation process.

[14] More information about and data from the Ethiopian Socioeconomic Surveys (ESS) of wave 1 – 3 done in 2011, 2013 and 2015 can be found at the World Bank's website – in the Living Standards Measurement Study (LSMS) category of Central Microdata Catalog: http://microdata.worldbank.org/index.php/catalog/lsms.

[15] *id* stands for identification.

4.3 Descriptive Statistics

The study considers data only from four major regions of Ethiopia – Tigray, Amhara, Oromia and SNNP regions. The exclusive focus on these four regions is due mainly to – i) the ERSS sample is representative for these regions, ii) over 90 percent of the country's population lives in these four regions; and iii) enormous production levels of agricultural outputs, for example, in the 2016/17 main agricultural production season, these four regions represented 97 percent of area of grain crop land, 97 percent of grain crop yield, 93 percent of total livestock population (in TLU), and 94 percent of total number of beehives in Ethiopia (CSA and WB, 2013 and 2017). Table 1 illustrates the distribution of sample smallholders across regions and farm specializations.

Table 1. *Households in crop productions and livestock activities by region*

Region	Number of households	District (woredas)	percent of HHs by Type of Farm by region		
			Crop	Livestock	Mixed
Tigray	151	9	11	4	85
Amhara	349	17	9	1	90
Oromia	247	17	6	2	92
SNNP	410	13	5	0	95
Total	**1157**	**56**	**7**	**1**	**92**

Source: CSA (2013, 15, 17)

The panel data consists of 3,465 observations (1,155 households) spread over three years (2011, 2013 and 2015). The average value of agricultural outputs is ETB 5,365.17 per annum (See Table 6 in Appendix 8.4). The corresponding standard deviation is ETB 5,817.88, which is an indication of significant variability in the value of agricultural output among households under study. Similarly, as indicated in Table 6, a similar pattern is also observed for total variable costs and average livestock herd size. The average land size owned by sample households is approximately 1.1 hectares at national level. The average family labor (in adult equivalent) and number of traditional ploughs owned by households is 3.33 and 0.91 respectively.

As presented in Table 6 (Appendix 8.4), the average age of household heads under study is 45.25 years. Twenty percent of the sample household heads are female while the remaining sixty percent households are male headed. As indicated, 46 percent of sample households were negatively affected by shocks which includes death of family member (mainly bread earner), flood, drought, etc. A quarter of sample households have been involved in off-farm activities. It is also shown that around an average of 28 percent of target households have received credit in each year. Majority of the households under study practice crop rotation, 88 percent. On average 9 percent of the sample households own at least one beehive.

Moreover, as the study also focuses on examining the regional patterns of technical efficiency scores, it is reasonable to provide detail analysis based on regional level descriptive statistics. In Appendix 8.5, a detail illustration of summary statistics of regional level data is provided in order to be able to see how variables behave across regions.

5. Empirical Strategy

The Econometric Specification

In agricultural economics literature, different functional forms (e.g., Cobb-Douglas and translong) are usually used to estimate agricultural production frontiers. Researches on developing countries technical efficiency have mostly used Cobb-Douglas functional form, though it has been generally concluded that choice of functional form does not affect the technical efficiency scores (Thiam *et al.*, 2001).

Following Battese and Coelli (1995), a stochastic frontier production for panel data is presented (i.e. Cobb-Douglas functional form for simplicity of estimation and interpretation of parameters):

$$Y_{it} = f(x_{it};\ \beta)\exp(v_{it} - u_{it}) \qquad i = 1, 2, \dots, N\ t = 1, \dots, T \qquad (15)$$

where the technical inefficiency term is identified as

$$u_{it} = f(z_{it}; \delta) \qquad i = 1, 2, \dots, N\ t = 1, \dots, T$$

where: Y_{it}: is output at time t by the i^{th} farmer;

x_{it}:	(1×k) vector of inputs to produce output Y
β:	(k×1) vector of unknown parameters
v_{it}:	random errors independently distributed of the $u_{it}s$
u_{it}:	non-negative random variables associated with technical inefficiency of production
z_{it}:	(1×m) vector of explanatory variables associated with the technical inefficiency
δ:	(m×1) vector of unknown coefficients of the inefficiency model

The production frontier is specified as;

$$T_{output} = (Land, TLU, TVC, F_{Labor}, Agroecology, Year\ )$$[16]

Real value

In order to account for price inflation, GDP deflator – with 2010 base year price – has been used to calculate the real monetary values of different agricultural (by)products and inputs utilized using data from the IMF's website[17]. GDP deflator is used because it provides comprehensive measure of inflation as it covers all goods and services in the economy, whereas data on Consumer Price Index (CPI) considers a specific basket of goods and services.

The dependent variable, T_{output}

T_{output}: = the estimate of total monetary value (i.e. in ETB[18]) of agricultural products by a given farm household in year t. The total value of farm output included crop output, sale of live animals, and sale of livestock (by)products (all in monetary term). The monetary value of total crop output by a given farm household is an aggregation of all types of crop (in monetary term) produced by the household. The calculation is done using a zonal (mostly), regional, or national level crop-specific prices upon availability data. The livestock sale, if a farmer has sold any in year t, is the revenue earned from sale of any type of live animals

[16] The identification of output and input variables in crop and livestock production satisfies the basic properties of production function. Production function has basic properties of non-negativity, weak essentiality, non-decreasing in x, and concave in x. These properties, however, are neither exhaustive nor universally maintain. (see e.g., Coelli *et al.*, 2005).
[17] http://www.imf.org/external/datamapper/datasets
[18] ETB stands for Ethiopian Birr – a national currency of Ethiopia. currently 1USD = 27.92 ETB (based on exchange rate available at the Ethiopian national bank – https://www.nbe.gov.et/market/banksexchange.html – on August 5, 2018).

including, cattle, sheep, goats, horses, donkeys, mules, and chicken. Sale of Livestock (by)product is the revenue earned by a given farmer from actual sale of livestock (by)product including, eggs, honey, milk and milk products, meat, and animal skin. The income from livestock and livestock (by)products is calculated using the method of the FAO Rural Livelihoods Information System (RuLIS)[19]. The only difference with the RuLIS is that the current aggregation didn't consider the value of self-consumed livestock (by)products due to data unavailability.

Production Inputs, vector of x_{it} and expected signs

As clearly discussed in section 1.1, a single stochastic frontier is chosen instead of sub-sector efficiency analysis methods in order to make sure that the model is not suffering from omitted variable bias or to avoid errors in identifying the inputs with the right amount for the sub-sector production. In this model, all farm inputs are included using appropriate units. The following input variables are used for the whole-farm production of a given farm household;

$Land$: $=$ area of land owned by the household in square meters. Land is used to grow different crops and crop residues are used for livestock feeding. Land is expected to have a positive sign as in (e.g., Bagi and Huang, 1983; Tirkaso, 2013)

TLU: $=$ total number of livestock owned by the household are included. This includes virtually all categories of livestock which are common to Ethiopian smallholders except camel (camels are mostly found in the pastoralist area). Cattle, small ruminants (sheep and goats), non-ruminant grazing animals (donkeys, mules, and horses) and chickens are included in the study. In order to have a common unit of measurement, TLU[20] (Tropical Livestock Units) has been used to aggregate total livestock herd size owned. TLU is expected to have a positive sign in the production function.

TVC: $=$ total variable cost (in monetary terms – ETB) incurred by a given farm household for crop and livestock production in year t. TVC includes, cost of fertilizer, veternary expenses, and other miscellaneous expenses. TVC is also expected to positively correlated with the dependent variable, T_{output}.

F_{labor}: $=$ family labor – number of adult members of a given farm household in year t. Family labor is measured in terms of adult equivalent[21].

Control Variables

Control variables are included in order to capture variations in output and inputs due to due to different agro-ecological characteristics of locations of sample smallholder farmers and weather condition variations over years. Agro-ecological zones are categorized into four major groups in order to control for differences due to several environmental, topographical, and other variations across different places where sample households are located in. Following Battese and Coelli (1995), year variables are included to capture changes over years, though no significant technological change is expected to exist within five years period of time.

[19] A detail procedure in aggregating the income from livestock and livestock (by)products can be found in FAO, 2018.

[20] The TLU is calculated based on the TLU equivalent conversion factors for each category of livestock. The conversion factors are 0.7 for cattle, 0.8 for horses, 0.7 for mules, 0.5 for donkeys, 0.1 for goats and sheep, and 0.01 for chicken (see Janke, 1982).

[21] Following Fletschner and Zepeda (2002 p.559) different weights are used for different age groups in the family - ages 4-5 = 0.1, ages 6-8 = 0.3, ages 9-12 = 0.5, ages 13-17 = 0.8, ages 18-59 = 1.0, ages 60-65 = 0.8,ages 66-75 = 0.5, and ages 76-80 = 0.3.

$Agroeco_{zone}$: = four major agro ecological zones are categorized in this variable – tropic warm, tropic cool semi-arid, tropic cool sub-humid, and tropic cool humid.

$Year$: = data on each farm household under analysis is observed on year 2011, 2013, and 2015.

Technical efficiency and exogenous determinants of inefficiency

Alike most stochastic frontier models, the main objective of this thesis is to estimate whole-farm technical efficiency of target farmers and examine determinants of inefficiency. Once the model parameters are estimated, household-specific efficiency are estimated and mean technical efficiency is also computed.

Examining the effects of farmers' inefficiency determinants is also an important input in the process of policy formulations or planning development projects. Accordingly, the relationship between the estimated inefficiency scores and important exogenous variables is evaluated. In order to do that, Kumbhakar *et al.* (2015) showed that the term σ_u^2 can be treated as a function of a set inefficiency determinants (z_i). Two-step or single-step procedures have been used to investigate the relationship between inefficiency and determinants in technical efficiency literature. Single-step approach parametrizes σ_u^2 (the distribution function of u_i) as a function of the explanatory variables (z_i) – so that the z_i (exogenous variables) are allowed to influence the level inefficiency scores. The two-step approach obtains firm-specific inefficiency scores in the first step and then regress the index on the set of explanatory variables (z_i) in the next step. This approach has been criticized since the results may be biased in case that the inefficiency determinants (z_i) are correlated with input variables (x_i) (Kumbhakar *et al.*, 2015). Despite this critical point, several papers have been using the two-step approach by logically or intuitively justifying that this approach would be appropriate (for instance Hansson and Öhlmér, 2008). Yu (1998) also noted that either of the methods would be appropriate depending on the situation. She further argued that a two-step approach is preferable in a scenario where sample producers are operating in a very different environment since it correlates the exogenous variables directly to the level of producer's technical efficiency. Thus, this thesis also uses the two-step approach since the sample households are operating in a heterogeneous systems due to significant variations in agro-ecological zones, terrain roughness, weather conditions and also different specializations within the crop-livestock system.

Accordingly, the estimated technical inefficiencies of individual farm households are then treated as dependent variable to analyze the effects of different factors associated with farm management strategies or other factors. Table 8 in Appendix 8.7 summarizes the variables which are included as determinants to the technical inefficiencies with their expected signs.

6. Result and Discussion

Before going directly to the panel data analysis, pooled data and cross-section data analyses are done as a baseline for the main analysis, panel data analysis. Baseline econometric analyses are discussed in detail and presented in Appendix 8.8. The baseline analyses helps us to determine appropriate variables, to make sure that basic properties of production function are satisfied, and in order to get different insights or implications to the panel data model. The baseline econometric results, namely, COLS and cross-section models provided some insights about the appropriateness of included variables, presence of technical inefficiency, the need for nonlinear model and distributional assumption, variation in technical efficiency scores over years, and consistency of signs of estimated coefficients over years. These issues were taken into consideration under the main model of interest. For example, cross-section models provided significantly different mean technical efficiency scores for different years but the same sample smallholder farmers (see Table 10 in Appendix 8.8). So that time-variant model is appropriate because it assumes that efficiency score of a given farmer changes over time. In addition, the distribution of OLS residuals is skewed to the left (see Figure 8), indicating that stochastic frontier model need to be estimated because the OLS is not an adequate representation of the data.

The main model of interest for this study is the time-varying random effects model as explained in section 3.4. This analysis is done using a panel data with 3,465 observations over three years. The econometric estimates of this model (see Table 3) are consistent with alternative models, the COLS and cross-section data models which are discussed in detail in Appendix 8.8. The descriptive statistics, COLS, and cross-section SF analysis introduced us to the data and helped us to get "advanced" insights on what to expect from the panel data model results. Apart from small changes in the magnitude of estimated parameters, different models provided more or less comparable econometric results. Moreover, the time-invariant model is presented in Table 3 in order to show that there are no significant changes in the estimated econometric results. Thus, these consistencies of econometric estimates across different models indicates that econometric results are robust.

Recall the specific objectives of this study, (i) estimation of technical efficiencies, (ii) analysis of inefficiency determinants, and (iii) analysis of patterns of technical efficiencies across regions and different landholding and livestock holding sizes, are addressed in the following subsections. The research question – what level of increment in agricultural output of sample smallholder farmers would be possible with the existing technology and given level of inputs? – is also addressed.

6.1 Frontier Production

As explained in section 4.3, the time variant random effects model (Battese and Coelli, 1995) is utilized to estimate the panel data SF production model (see column 1 in Table 2). Estimates of the model were obtained using maximum-likelihood procedures using the STATA program. The econometric estimates from the time-invariant counterpart are also presented (second column) in order to show there are no significant differences in the size and signs of estimated parameter coefficients.

Detailed discussion of the econometric results are based on the main model of interest, the time-variant random effects model (column 1 of Table 2), because of aforementioned theoretical justification (see section 4.3). As in the cross-sectional SF model, $\lambda(lambda)$ is greater than one and statistically significant at one percent, which confirms the existence of technical inefficiency. The estimate for the variance parameter, γ[22] $(gamma)$, is calculated to be close to one, which indicates the inefficiency effects are highly significant. Thus, the discrepancy between the observed output by sample smallholder farmers and estimated frontier as a whole is explained by the technical inefficiency rather than by the random influences.

In general, the estimated coefficients in the model have positive signs and sizes which is consistent with expectations and the previous results from the two models, COLS and cross-sectional SF model. As in the COLS and Cross-section SF models, the coefficients of input variables add up to greater than one, which implies increasing return to scale.

***Output elasticities*[23]**

All output elasticities are positive and statistically significant at one percent level of significance with the exception of weighted family labor (Ln_F_Labor). The mean output elasticities for sample smallholder farmers are calculated by substituting all input values at their sample mean. Of all input variables, area of land (Ln_Land) has the highest effect on total value of agricultural output with an elasticity equal to 0.37. That means, a 1 percent increase in the area of land results in an estimated increase in agricultural output of 0.37 percent. The estimated coefficient of land is consistent with technical efficiency studies conducted in Ethiopia (e.g., Alene and Hassan, 2003b; Haji and Andersson, 2007; Ahmed *et al.,* 2014 have estimates of parameters with more or less similar magnitude and signs). As expected, the coefficient of total livestock size (in TLU), LN_TLU, is estimated to be positive and the corresponding output elasticity is 0.325. Meaning, a one percent increase in the mean size of livestock owned by sample household is associated with a 0.33 percent increase in the mean of value of total agricultural output, which is consistent with, e.g., Cabrera *et al.* (2010). The next highest elasticity is number of traditional ploughs owned by smallholder farmers, Ln_tr_plough (0.276), followed by total annual variable cost incurred for crop-livestock production, Ln_TVC (0.053). Abebe (2014) also estimated farm tools, which includes traditional plough, to be positive and statistically significant at one percent significance level. Likewise, the positive and significant coefficient of total variable cost is consistent with multiple studies on farm technical efficiencies (e.g., Bagi and Huang, 1983; Wubeneh and Ehui, 2006; and Battese and Coelli 1995). The output elasticity of family labor, Ln_F_Labor, is estimated to be positive, though it is not significant at less than ten percent probability level. The insignificant labor productivities in smallholder farming systems is consistent with the results of related studies (Wubeneh and Ehui, 2006; and Haji and Andersson, 2007).

Other control variables

As explained in section 4.3, $Agroecology,$ and $Year$ are included in the stochastic frontier in order to capture heterogeneity due to differences in agro-ecological zone, and year – for more accurate econometric estimates of the frontier production. $Agroecology$ is the a categorical variable, hence the three categories – tropic cool semi-arid, tropic cool sub-humid, and tropic cool humid – are assessed with reference to the tropic warm zone. The coefficients of the tropic cool semi-arid, tropic cool sub-humid have positive and negative signs respectively, meaning smallholder farmers living in these agro-ecological zones tend to have higher and lower level of agricultural production as compared with farmers living in tropic warm zone, but it is not statistically significant at ten percent level of significance. The coefficient for tropic cool humid agro-ecological zone is -0.266 and it is statistically significant at one percent level of significance. Meaning, sample smallholder farmers who are located in tropic cool humid agro-ecological zone produce 26.6 percent

---

[22] Note: the key parameter $\gamma\ (gamma) = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$, is bounded between one and zero, where $\gamma = 1$, there is no random error and where $\gamma = 0$, technical inefficiency does not exist (Battese and Coelli, 1995).

[23] Note: interpretation of output elasticity due to a change in each independent variable is based on the assumption that other factors are remained constant.

less (in monetary terms) as compared with other sample farmers who are located in the first three agro-ecological zones. $Year$ indicates the value to agricultural output has tended to increase over the five years period which is consistent with the higher rate of agricultural growth reported by the Ethiopian government and World Bank (see e.g., NBE, 2017; WB, 2017: and Bachewe *et al.*, 2015).

Table 2. *ML Estimate of Frontier Production.*

Variables	**Labels**	**Time varying random effects model**	**Time invariant random effects model**
Frontier Production			
Ln_TVC	*Total variable cost for agricultural production*	0.0528***	0.0651***
		(0.00573)	(0.00695)
Ln_TLU	*Livestock herd size owned in TLU*	0.325***	0.361***
		(0.0329)	(0.0405)
Ln_Land	*GPS/Rope-and-Compass measured area of land (sqm)*	0.370***	0.436***
		(0.0193)	(0.0231)
Ln_F_Labor	*Family labor measured in adult equivalent*	0.0465	0.0238
		(0.0538)	(0.0672)
Ln_tr_plough	*No of traditional plough owned by the HH*	0.276***	0.266***
		(0.0495)	(0.0588)
Agro-ecological zone			
Tropic cool semi-arid		0.0801	0.131
		(0.103)	(0.131)
Tropic cool sub-humid		-0.0422	-0.0267
		(0.101)	(0.129)
Tropic cool humid		-0.266***	-0.279**
		(0.103)	(0.131)
Year			
Year 2	*year = 2013*	0.760***	1.005***
		(0.0417)	(0.0440)
Year 3	*year = 2015*	0.728***	0.862***
		(0.0406)	(0.0430)
Constant		4.238***	3.004***
		(0.202)	(0.239)
sigma_u		13.221*	
		(7.0380)	
sigma_v		0.620***	
		(0.0184)	
lambda		21.355***	
		(7.0371)	
Sigma 2			296.713
gamma			0.997
sigma_u2			295.757
sigma_v2			0.956
Number of Observations		3199	3199

*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

6.2 Technical Efficiency Estimates and Distribution

Table 3 presents the distribution of calculated technical efficiency of sample smallholder farmers. The predicted technical efficiencies ranged between 0.1 percent and 89 percent with the overall sample mean equivalent to 53 percent. This implies that, in the short run, there are opportunities for the average farmer in the sample for increasing agricultural production by if the average farmer in the sample by 40 percent by performing the best practice of the most technically efficient farmer, i.e. $1 - \left[{}^{0.532}/_{0.887}\right]$.

Moreover, as shown in Table 3, few small farms (3.8 percent) found to be more technically efficiency with a corresponding score greater than 80 percent. Large number of farmers, 43.7 percent of the total sample, have a technical efficiency score within the range of 61 and 81 percent. 28 percent of the sample smallholder farmers possess a technical efficiency score of 41 to 60 percent, followed by the third largest category with 14.4 percent. The number of small farms operating at less efficient levels than twenty percent is about ten percent. The distribution of technical efficiency scores is also presented in Figure 9 (Appendix 8.9) using a histogram.

Table 3. *Mean and frequency distribution of technical efficiency.*

Technical Efficiency percent	Smallholder farmers					
	Number	Percent	Mean	SD	Min	Max
<=20	321	10.03	0.0997	0.0584	0.0014	0.1999
21 - 40	459	14.35	0.3124	0.0583	0.2012	0.3997
41 - 60	899	28.10	0.5111	0.0560	0.4003	0.5995
61 - 80	1,397	43.67	0.6914	0.0542	0.6002	0.7998
>80	123	3.84	0.8234	0.0178	0.8002	0.8870
Sum percent	**3199**	**100**	**0.5320**	**0.2077**	**0.0014**	**0.8870**

6.2.1 Technical Efficiency across Different Landholding and Livestock holding sizes

Several studies attempted to examine the relationship between farm size and technical efficiency of farms (e.g., see Rezitis *et al.,* 2002; Heshmati and Mulugeta, 1996; and Squires and Tabor, 1991). Though the landholding size does not have significant variability across the sample smallholder farmers, this thesis still tries to examine the correlation between different ranges of area of land size and mean technical efficiency scores within that group. The landholding size is grouped into five major categories. As can be seen from Figure 3(a), the distribution of estimated technical efficiency scores appear fairly constant across landholding sizes, which is consistent to the findings of Squires and Tabor (1991). However, smaller farm sizes still tend to be associated with relatively smaller technical efficiency scores. This positive relationship could be due to the fact that households with smaller land sizes are more likely to be involved in off-farm activities in order to fill gaps in their basic needs including food. In support of this, Beyene (2008) noted households in rural areas are commonly forced to look for off-farm activities due to smaller farm size. In addition, some development projects could be one of the sources of technical inefficiency since poor households are usually employed for physical work. For example, '*small landholding*' was one of the major criteria for inclusion of beneficiaries to the Productive Safety Net Program, one of the largest national level food security programs (Sharp *et al.,* 2006). A dummy variable which indicates whether a household is involved in off-farm activities or not is included as one of inefficiency determinants in the next section.

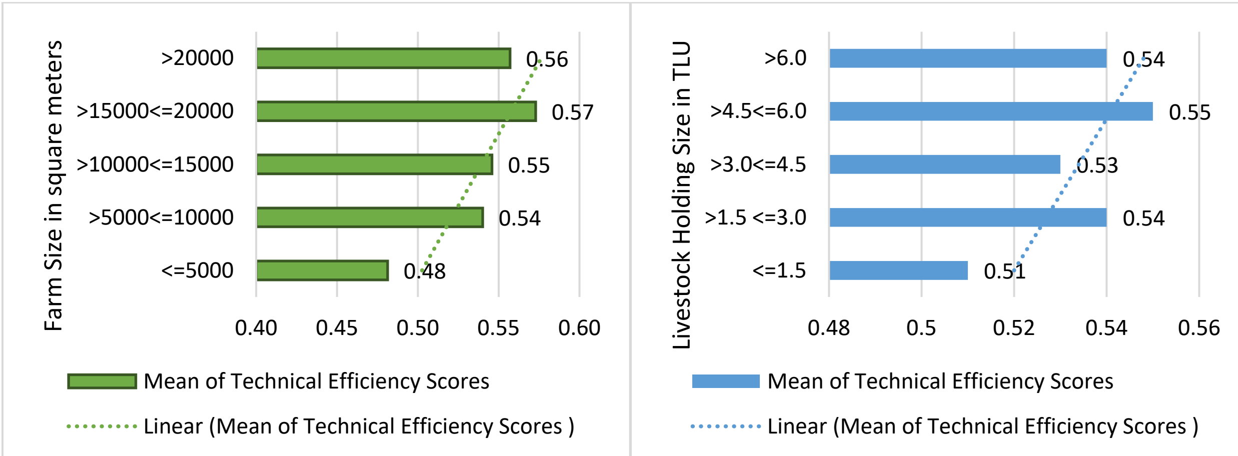


Figure 3. Distribution of technical efficiency across different (a) landholding and (b) livestock holding sizes.

Likewise, as shown in Figure 3(b), mean of estimated technical efficiency scores among sample smallholder farmers are more or less evenly distributed across different ranges of livestock holding sizes. Households with smaller livestock holdings tend to be slightly less technically efficient. The intuition behind these households would be the same as those who have higher technical inefficiency coupled with smaller landholdings. The general idea is, the smaller the sizes of livestock holdings and landholdings, the smaller would be the intensity of efforts on livestock and crop production – lower agricultural productivity. Nevertheless, further investigation is required to reveal the real cause of such small variations in technical efficiency scores across farm sizes and livestock holdings by taking several factors into consideration.

6.2.2 Technical efficiency across administrative regions and zones

Technical efficiency might also vary by region and/or zonal level divisions (e.g., see Squires and Tabor, 1991; and Tirkaso, 2013). Distribution of mean of predicted technical efficiency values is presented by 54 zones, where the sample smallholder farmers are located (see Figure 10 in Appendix 8.10 for detailed illustration).

Table 4. *Regional mean technical efficiency*.

	Number of			
Region	**Zones**	**Districts (Woredas)**	**Observation**	**Mean technical efficiency**
Tigray	5	9	450	52 percent
Amhara	11	17	1,056	57 percent
Oromia	17	17	738	54 percent
SNNP	21	13	1,230	50 percent
Total	**54**	**56**	**3474**	53 percent

Region wise, average technical efficiency ranges on average from 50 percent in SNNP, the lowest score, to 57 percent in Amhara regions, the highest one (see Table 4). Oromia region (54 percent) comes at the second place, in terms of average technical efficiency values exhibited by sample smallholders, followed by Tigray region where sample farmers have a mean technical efficiency of 52 percent. When we come to zonal level assessment, we find significant variation in average technical efficiency scores of sample smallholder farmers which ranges from 33 percent to 62 percent percent. As illustrated in Appendix 8.10, sample farmers from Horo Gudru Welega zone of Oromia region are the most technically efficient ones on average. North Shewa zone (62 percent) of Amhara region and West Arsi (62 percent), East Shewa (62 percent) and West

Shewa (61 percent) zones of Oromia region are among the top five zones where sample farmers from these zones are more technically efficient as compared to other farmers living outside of these zones. On the other hand, Burji special district (33 percent), South Omo zone (36 percent), Sheka zone (42 percent), and Gurage zone (44 percent) in SNNP region and West Wollega zone (44 percent) of Oromia region found to be represented by most technically inefficient sample smallholder farmers[24][25]. Consistent to this finding, Mekonnen (2013) found substantial variation in location-specific mean technical efficiency scores ranging from 46.4 percent in one of the study sites in Tigray region to 69.2 percent in one of study sites in SNNP region. Likewise, Tirkaso (2013) found mean technical efficiency scores varying from 33 percent in Imdibir study site of SNNP region to 45 percent in Yetmen study site in Amhara region.

6.3 Inefficiency Determinants

The maximum-likelihood estimate for the determinants of farmers' technical inefficiency level indicates is presented in Table 11 – in Appendix 8.11[26]. The coefficient of ***Year*** of observation is estimated to be negative and highly significant, which implies levels of technical inefficiency effects of sample smallholder farmers were less in 2013 and 2015 production periods as compared to the 2011 similar season. One thing we should be aware of is that these year dummy-variables may be picking up the effect of other factors which are not included as explanatory variables to the inefficiency model. For example, there have been enormous improvements in supply of improved agricultural inputs[27], which could vary year-to-year both in type and quantity. This negative relationship between year dummy-variables and the technical inefficiency effect is consistent with Coelli and Battese (1995, 1996), and it somehow confirms the agricultural productivity growth which has been reported by the Ethiopian government and international development organizations (see e.g., NBE, 2017; WB, 2017; and Bachewe *et al.*, 2015).

As expected, ***hhh_sex*** have a positive coefficient with one percent level significance indicating male headed households tend to be less inefficient as compared to female headed households which is similar to similar studies (e.g., Abebe, 2014). It can be interpreted as, male headed households are likely to be less inefficient by 0.027 percent than female headed households keeping other factors constant. Even though the effect is not statistically significant, age of the household head (***Ln_Age***) has a positive coefficient which indicates older farmers are more inefficient. This finding is consistent with technical efficiency studies conducted in Ethiopia, e.g., Ahmed *et al.* (2014); Wubeneh and Ehui (2006); and Alene and Hassan (2003a).

The effect of credit use on technical inefficiency of smallholder farmers has been examined in several technical efficiency studies conducted in Ethiopia, e.g., Ahmed *et al.* (2014); Alene and Hassan (2003a); and Asefa (2011) estimated credit use to be statistically significant and negatively correlated with inefficiency term. Komicha and Öhlme (2006) analyzed the effect of credit on technical efficiency of farmers in the southern part of Ethiopia by explicitly focusing on estimating and comparing technical efficiency of credit-constrained (CCFHs) and unconstrained farm households (CUFHs) by employing a stochastic frontier technique. They also found credit-constrained households are twelve percent less efficient that credit unconstrained households. Consistent to these findings, this thesis found that the use of credit (***Credit_user***) tends to negatively affect farmers' technical inefficiency. Thus, credit user sample smallholder households are 0.043 percent less inefficient relative to credit non users.

[24] Note: Zonal or district level averages of technical efficiency scores of sample farmers is provided in Appendix 8.10.
[25] The percentage values in parenthesis are averages of predicted values of technical efficiency scores of each smallholder farmer in the respective district, zone, or region.
[26] Note: these results can also generated using OLS because both ML and OLS give similar estimates for large sample.
[27] The supply of improved agricultural inputs has been provided or facilitated by development projects/programs or agencies which are listed in section 4.1 or other unmentioned initiatives.

As explained in section 5.2, households involved in off-farm activities aside to their farming activities have a tendency to be more inefficient. The finding in Table 11, confirms this since ***Off_farm_d*** have a positive coefficient though it is not statistically significant. For sample smallholder farmers those who are involved in off-farm activities within the period of the study, there is a tendency to be more inefficient as compared to those who do not participate in off-farm activities. This finding is consistent with Asefa (2011).

The coefficient for the dummy variable, ***Beehives***, which is an indicator for owning at least one beehive, found to be negative and statistically significant at one percent level of significance. It is not common to examine the effect of beekeeping on technical (in)efficiency of smallholder farmers. Asefa (2011) included beehives in aggregating total livestock size, which was then included as inefficiency determinant. However, this approach would be misleading in terms of investigating the net effect of beekeeping since it would be dominated by the effect of other livestock types. Pender and Gebremedhin (2007) concluded households who have beekeeping as additional source of income in addition to farming, earn significantly higher income than households who do not have beehives. This inference make sense because beekeeping is less demanding in terms of labor use as well as utilization of other inputs. Moreover, Table 11 indicates households who have beekeeping as an additional source of income are less inefficient by 0.035 percent than their counterparts with no beehive(s). So to conclude, small farm holders with a mixed-farming operations including beehives tend to be more efficient.

In line with the expectation, ***Shock***, found to be positively related with technical inefficiency score. For example, if an adult member of a household dies, agricultural production tend to decline due to lesser labor use. Hence, controlling this such factors is important. As can be noticed in Table 11, households who were negatively affected by some kind of shock found to be more technically inefficient (by 0.026 percent) as compared to those who were not affected.

Ahmed *et al.* (2014) found crop-rotation practice to be negatively related to technical inefficiency similar to the result in Table 11, but the coefficient was not statistically significant. In this thesis, however, the negative coefficient (of ***Crop_rotation***) is statistically significant at one percent level of significant. The implication is that a smallholder farmer who does not practice crop rotation can reduce its inefficiency by 0.043 percent if he starts to practice crop-rotation.

Several farming technical efficiency studies in Ethiopia concluded that level of household heads' education, mostly in terms of number of years of education, is negatively associated with their respective technical inefficiency (e.g., Ahmed *et al.*, 2014; Fita *et al.*, 2013; Tirkaso, 2013; Ahmed *et al.*, 2013; and Asefa, 2011). However, counting just the number of years which the household head has been in school might be problematic. The reason is, the more an individual is educated (above certain level of qualification) the higher the chance of being involved in local leadership roles or other employment chances. Hence, categorizing educational qualification is more important in order to identify which level of educational qualification is better in terms of farming technical efficiency for more precise policy recommendation. As illustrated in Table 11, the coefficients for household heads, who are educated up to both fifth through eighth and ninth through twelfth grades, are negative though they are not statistically significant. This implies farmers who completed from fifth through twelfth grade are likely to be more technically efficient (i.e. less technically inefficient) as compared to those who only completed grade 4 or lower grades. Household heads who are educated at the level of above twelfth grade are less efficient (more inefficient) by 0.051 percent. This could be due to the reason that individuals with some kind of relatively higher educational qualification (twelve plus years of education), have greater chance to be involved in local leadership roles, to own off-farm business, or to be employed in the nearer town.

Moreover, the “Region” variables are included in the regression in order to control location-specific factors. Table 11 indicates sample smallholder farmers located in Amhara and Oromia region are more technically efficient (less in efficient) by 0.065 and 0.046 percent respectively as compared to those who live in Tigray region. The coefficients for Amhara and Oromia regions are statistically significant at ten and five percent respectively. The coefficient for SNNP region is positive, implying smallholder farmers located in this region are technically less efficient (more inefficient) as compared to their counterparts living in Tigray region. However this positive coefficient of SNNP region is not statistically significant, which means average technical efficiency of sample smallholder farmers living in Tigray does not significantly differ from those who live in SNNP region. Moreover, regional pattern of technical efficiency of sample smallholder farmers is described in section 6.2.2.

7. Conclusion and Recommendations

This thesis used a random-effects stochastic frontier model to estimate the level of technical efficiency of smallholder farmers located in Tigray, Amhara, Oromia, and SNNP regions of Ethiopia. A panel data is employed with 1,155 sample smallholder farmers (3,465 total observations), where each farmer is observed three times, using agricultural and socioeconomic records of each farmer is used from year 2011, 2013, and 2015 production seasons. It has been justified that Cobb-Douglas functional form found to be more appropriate to represent the underlying technology. The determinants of the inefficiency component have also been examined in terms of their magnitude, sign of coefficients, and their consistency with previous studies with similar setups.

Prior to the aforementioned econometric model, descriptive statistics, COLS procedure, and cross-sectional data model have also been used in order to have better accuracy by taking the implications from the results of these models into consideration. For example, the COLS approach indicated maximum-likelihood estimation procedure would give more accurate estimates, and from the cross-sectional SF model, we learned taking time-trend variables (i.e. in the form of year dummies) would control for several unobserved factors varying over the selected five year period. Finally, a result from time-invariant panel data model is also presented, and apart from small differences in the magnitude of coefficients, it has been shown that no significant difference is observed between the two models – i.e. the time-varying and time-invariant. This was expected since the time-series is not too long.

The mean of estimated level of household-specific technical efficiency is 53 percent with individual efficiency scores ranging from 0.14 to 89 percent. This indicates if the average smallholder farmer was to achieve the technical efficiency level of the most efficient farmer, it could be possible to achieve a 40 percent (1-[0.53⁄0.89]) increment in value of output by average farmer. This increment can be achieved using the existing level of inputs. The distribution of technical efficiency scores across different sizes of landholding and livestock holdings revealed smallholders with small plot of land and/or small livestock holding size tend to be less technically efficient. In addition, sample smallholder farmers located in Amhara and Oromia regions tend to be more technically efficient as compared to their counterparts in Tigray region. Farmers from SNNP region are inclined to be less efficient than farmers located in Tigray region though this difference is not statistically significant. The year dummy variables indicated that average technical efficiency scores found to be higher in 2013 and 2015 relative to the same production season and for the same target in the 2011 production season. The input elasticities are calculated have positive signs and to be significantly different from zero at one percent level of significance. The only exception to this is the coefficient for family labor, which have a positive sign but not statistically significant at ten percent level of significance. The estimates of returns to scale is greater than one, indicating sample smallholder farmers have a production technology of increasing returns to scale.

Analysis of the relationship between technical inefficiency level and corresponding determinants revealed crop rotation, beekeeping, and credit use are important factors positively influencing the level of technical efficiency of smallholder farmers. The occurrence of negative shock, like death of household head or any other hazards, seem to significantly reduce farmers' technical efficiency. Male headed households found to be technically efficient as compared to their female counterparts.

It seems that some studies in developing countries agriculture have been putting policy recommendations in a "*dos and do nots*" and generic ways partly due to low level of understanding and limited data availability on different indigenous farming systems (e.g., see Hardaker and Fleming, 1989). However, it has been well noted in the literature that conclusions for policy recommendation should be based on extensive data sets on important variables for production frontier and inefficiency models (e.g., Battese and Coelli, 1996) for more precise policy remedies. Despite such risks of generalizations, the econometric results from this thesis suggest agricultural development policies would be in a better position to improve agricultural productivity if improving access to credit services, encouraging beekeeping, and promotion of crop rotation are included among prioritized activities. Best practice and experience sharing among farmers' organizations would also facilitate skills transfer among best and less performing farmers. The difference in the level of technical efficiency between male and female-headed households could be lessened by implementing appropriate women empowerment programs to make them equally efficient as their male counterparts. Given the government's and development organizations' massive efforts towards agricultural development, the positive coefficients for time-trend variables implies initiatives in the agricultural development are playing important role keeping other factors constant. Therefore, lessons need to be well documented and shared to a wide range of audience using appropriate communication tools. Expanding off-farm employment alternatives for individuals with relatively smaller size of landholding and livestock holdings could play a significant role to the country's economic development. This action will increase the land holding size of the remaining farmers, hence technical efficiency of these farmers will increase, and the economy can benefit from effective labor use from farmers who left farming in favor off-farm employment. Moreover, interregional experience sharing would also be important in order to minimize the gaps among the level of average technical efficiency of regions.

8. Appendix

8.1 Classification of Different Farming Systems and Agro-ecological Zones of Ethiopia

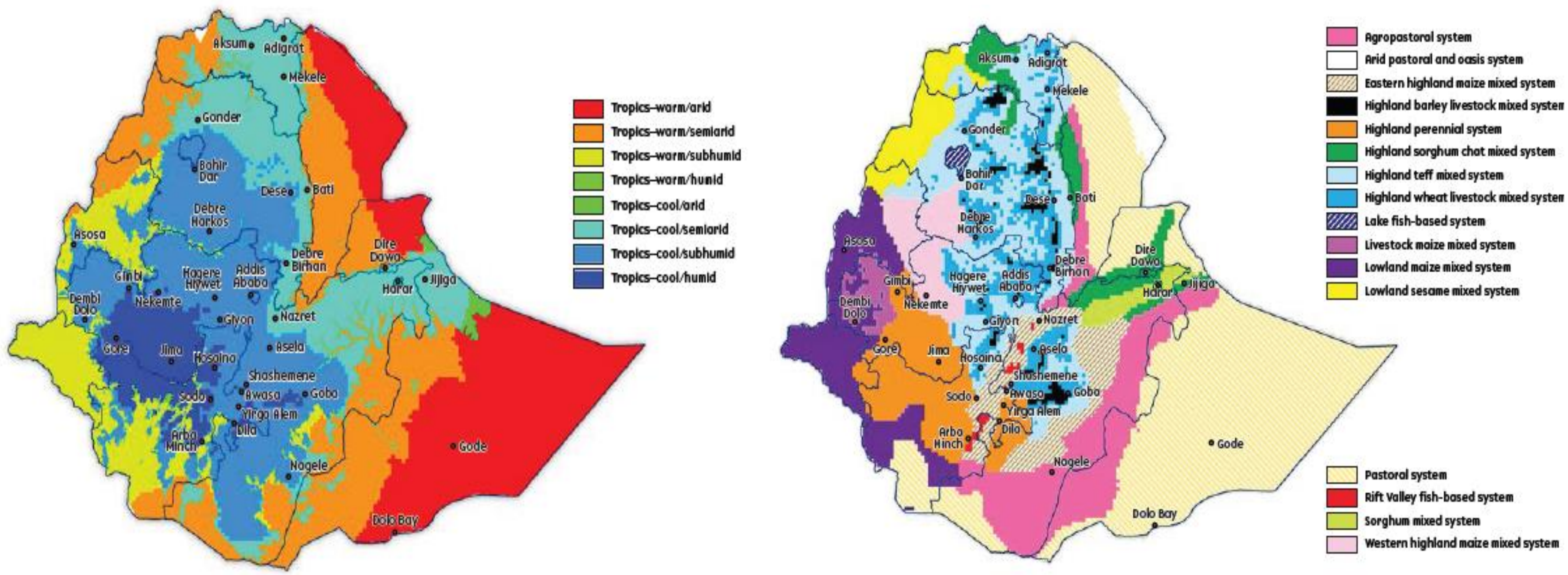


Figure 4. Classification of (a) agro-ecological zones and (b) farming systems in Ethiopia. (source: Amede *et al*., 2017).

8.2 Overview of empirical studies on farmers' technical efficiency, Ethiopia

Table 5. *Overview of empirical studies of smallholder farm technical efficiency in Ethiopia.*

Author(s) and year	**Product(s)**	**Sample size**	**Model**	**Inefficiency determinants**
Abebe (2014)	Multiple crops	1360	Cross-sectional – SFA*	Age, Household size, Gender, Education, Livestock, Soil Conservation, Extension, Irrigation, Manure, Off-farm income
Ahmed *et al.* (2013)	Multiple crops	200	Cross-sectional - S FA*	Age, Gender, Household size, Education, Off-farm income, Land, Livestock, Irrigation, Extension, Transportation, Social status, Soil fertility
Ahmed *et al.* (2014)	Maize	138	Cross-sectional - SFA*	Age, Education, Household size, Extension, Land, Livestock, Home to farm distance, Number of weeding, Home to market distance, Soil fertility, Off-farm income, and Crop rotation
Alene and Hassan (2003a)	Maize	60	Cross-sectional - SFA*	Farm size, Age, Extension, Credit, Literacy, Plot ownership, Plot quality, Timely availability of inputs
Alene and Hassan (2003b)	Multiple crops	150	Cross-sectional - SFA*	Age, Education, Literacy, Farm size, Credit, Share of maize-potato cropping, Livestock unit, and Distance to district market
Alene and Zeller (2005)	Multiple crops	53	DEA** and PDF***	Improved technologies, Education, Extension, and Credit
Alene *et al.* (2006)	Multiple crops	124	Cross-sectional – SFA* and DEA**	
Asefa (2011)	Multiple crops	326	Cross-sectional - SFA*	Age, Household size, Education, Dependency ratio, Gender, Literacy, Livestock, Land fertility, Extension, Irrigation, Off-farm income, Credit, Crop diversification
Croppenstedt and Demeke (1970)	Multiple Crops	344	Mixed coefficients approach	Gender, Average age of Household labor, Credit, Crop damage, Animal disease, Time to collect fire-wood, Time to collect drinking water, Adult Literacy, Primary education completed, and Number of Hoes owned
Fita *et al.* (2013)	Dairy farms	240	Cross-sectional - SFA*	Age, Education, Extension, Organizational participation, Mass media exposure, Training on dairy farming, Green fodder/dry fodder/concentrate feed consumed per cow, Veterinary and related expenses, Labor man hour per cow
Haji and Andersson, 2006	Whole farm	150	DEA**	Age, Household size, Education, Extension, Off-farm income, Land Fragmentation, Diversification, Farm Distance, Credit Access, Consumption expenditure, Assets, and Farm size

Komicha and Öhlme (2006)	Multiple crops	240	Cross-sectional - SFA*	Age, Household size, Education, Extention, Interest rate, Land Fragmentation, Credit Access, Household wealth
Makombe *et al.* (2017)	Multiple crops	434	Cross-sectional - SFA*	Age , Gender , Education, and Extension
Seyoum (1998)	Maize	40	Cross-sectional - SFA*	Age, Education, Extension
Tirkaso (2013)	Multiple crops	562	Cross-sectional - SFA*	Age , Gender , Education, Radio, Cell phone, Households commercialization index, and Market Off-farm income, Market, and Extension
Wubeneh and Ehui (2006)	Dairy farms	74	Cross-sectional - SFA*	Age, Gender, Literacy, Livestock training, Location, Credit

*Note: *Stochastic Frontier Approach. **Data Envelopment Analysis. ***Parametric Distance Function.*

8.3 The Maximum Likelihood Estimator (MLE)

The random-effects model can be estimated either by generalized least squares (GLS) or using the maximum likelihood (ML) method (see e.g., Kumbhakar *et al.*, 2015; and Schmidt and Sickles, 1984). The GLS technique is usually used for the standard random effects panel data models. The main property of the fixed effect and random effect panel data models is that no distributional assumptions are required. Nevertheless, using the ML estimator, it is still possible to impose distributional assumptions on the error terms and their independence on the regressors (Schmidt and Sickles, 1984). In the literature, the statistical noises (v_{it}) have commonly been assumed to be normally distributed while the inefficiency term, u_i, was assumed to have a half-normal distribution (Ibid.). According to Schmidt and Sickles (1984), using MLE, it is possible to have distributional assumptions on v_{it} and u_i, commonly normal for the former one and half-normal for the latter one. They further generalized that, as $N \to \infty$ regardless of T, MLE's are consistent and asymptotically efficient than the GLS estimator.

A model for maximum likelihood estimator is presented as (see Kumbhakar *et al.*, 2015 p.379),

$$\begin{aligned}
&y_i = f(x_{it};\, \beta) + \epsilon_{it} \qquad i = 1, 2, \dots, N \quad t = 1, \dots, T \\
&\epsilon_{it} = v_{it} - u_i \\
&v_{it} \sim N(0, \sigma_v^2) \\
&u_i \sim N^+(\mu, \sigma_u^2)
\end{aligned} \tag{6}$$

The likelihood function for observation i is written as (see Kumbhakar *et al.*, 2015 p.380),

$$lnL_i = constant + ln\Phi\left(\frac{\mu_{i*}}{\sigma_*}\right) + \frac{1}{2}ln(\sigma_*^2) - \frac{1}{2}\left\{\frac{\sum_t \epsilon_{it}^2}{\sigma_v^2} + \left(\frac{\mu}{\sigma_u}\right)^2 - \left(\frac{\mu_{i*}}{\sigma_*}\right)^2\right\} - Tln(\sigma_v) - ln(\sigma_u) - ln\Phi\left(\frac{\mu}{\sigma_u}\right) \tag{7}$$

where:

$$\mu_{i*} = \frac{\mu\sigma_v^2 - \sum_t \epsilon_{it}^2}{\sigma_v^2 + T\sigma_u^2} \tag{8}$$

$$\sigma_{i*} = \frac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + T\sigma_u^2} \tag{9}$$

By summing lnL_i over i, $i = 1, \dots, N$, one can obtain the log-likelihood function L for the given model. To estimate the MLE parameters, numerical maximization of the log-likelihood function is used.

Following Kumbhakar and Lovell (2000), inefficiency the i^{th} observation can be computed from the mean or the mode based on estimated values of the model parameters (Kumbhakar *et al.*,2015 p.248);

$$E(u_i|\epsilon_i) = \mu_{i*} + \sigma_*\left[\frac{\phi(-\mu_{i*}/\sigma_*)}{1-\Phi(-\mu_{i*}/\sigma_*)}\right] \tag{13}$$

and

$$M(u_i|\epsilon_i) = \begin{Bmatrix} \mu_{i*} & if\ \mu_{i*} \geq 0, \\ 0 & otherwise \end{Bmatrix} \tag{10}$$

8.4 National Data Summary Statistics

Table 6. *Descriptive Statistics of important variables, National.*

	Label	NO*	Mean	SD**
Year	year 2011=1, year 2013=2, and year 2015=3	3,465	2.00	0.82
Ttl_output	Total value of annual agricultural output in birr	3,465	5,365.17	5,817.88
TVC	Total variable cost for agricultural production	3,465	651.60	1,002.64
TLU	Livestock herd size owned in TLU	3,306	2.91	1.98
area_land	GPS or Rope-and-Compass measured area of land (Square meters)	3,338	11,014.12	8,373.44
F_Labor	Family labor measured in adult equivalent	3,465	3.33	1.38
No_tr_plough	no of traditional plough owned by the HH	3,465	0.91	0.67
Age	Age of the HHH in years	3,462	45.25	14.68
Sex	0 if the HHH is male and 1 if female	3,465	0.20	0.40
Shock	negative shock affected the HH, 0 if no and 1 if yes	3,465	0.46	0.50
Crop_rotation	1 if the HH practice crop rotation or 0 if not	3,437	0.88	0.33
Credit_user	whether the HH use credit (1) or not(0)	3,451	0.28	0.45
Off_farm_d	The household earned off farm income(1) or not(0) during the year	3,474	0.25	0.43
Beehives	The HH own beehives (1) or not(0)	3,465	0.09	0.28
Temp_ann_mean	Annual Mean Temperature (deg ºC * 10)	3,463	183.77	28.73
RF_avg_ttl	Average 12-month total rainfalls(mm) for Jan-Dec	3,463	907.12	265.19

*Note: *Number of observation. **Standard Deviation. HH(H)=Household (Head).*

8.5 Descriptive statistics of data by region

As described in section 4.3, the first four largest regions (in terms of agricultural output and population) are included in this study. Table 7 presents summary statistics of output, input, and efficiency determinant variables for each selected region. As in the national data set, units in the regional data sets are observed over the three years. SNNP has the largest number of observations (1,230) in the sample followed by Amhara region (1,047). The remaining 741 and 447 observations are included from Oromia and Tigray regions respectively. The average agricultural output values (in monetary terms) are high in Amhara and Oromia regions – ETB 6,468 and 6,200 per annum, respectively. Similarly, households from Tigray region have an average farm output equivalent to ETB 5,409 followed by the least one, SNNP which has an average value of ETB 3,908. As for in the national data set, the standard deviations in Tigray, Amhara, Oromia, and SNNP regions is 5,873; 6,054; 6,633; and 4,650 respectively which all indicates a significant variability in average value of agricultural outputs per annum across all regions. The highest annual average variable cost is incurred by sample households from Amhara region (ETB 804) followed by households from Tigray, Oromia, and SNNP regions with average of total variable cost amounting ETB 804, 695, and 472 respectively. Nevertheless these variations in the average of total variable cost across regions, the TVC-output ratio is almost similar.

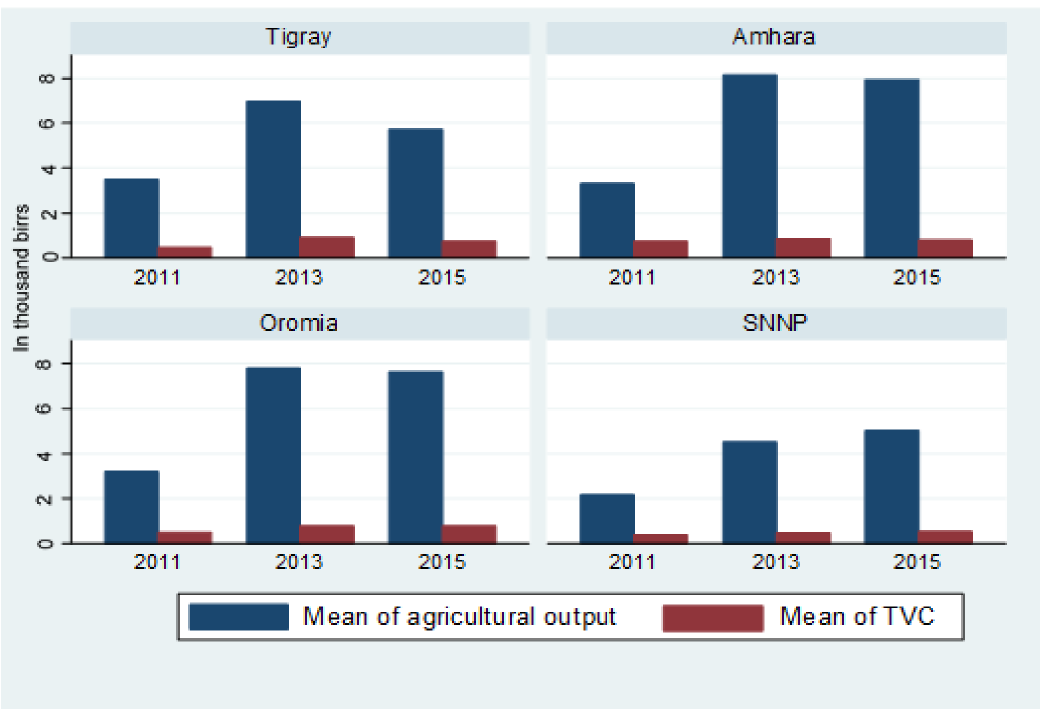
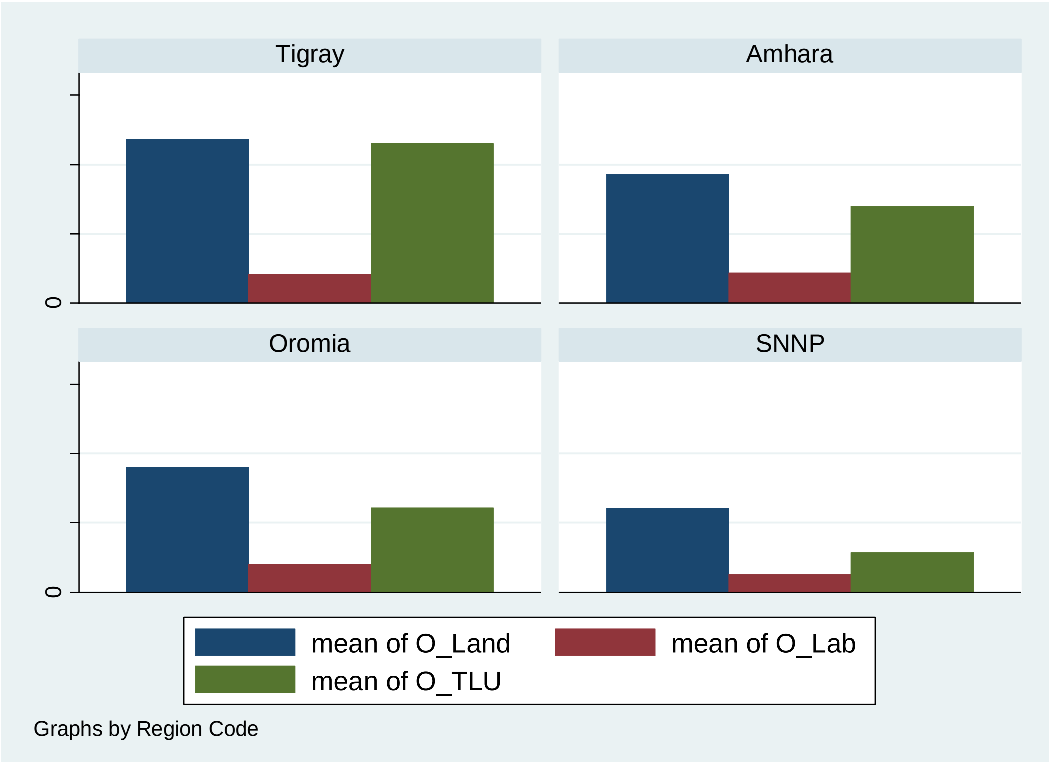


Figure 5. Annual average agricultural output and total variable cost among sample households, by region.

Sample households from Oromia region seem more cost effective with eleven percent TVC-Output ratio, whereas Amhara and SNNP have twelve percent each, and sample households from Tigray seemed to be less effective, thirteen percent. As it can be noticed in Figure 5, average agricultural output is significantly low (below ETB 4,000) in 2011 compared to 2013 and 2015 across all regions. This is not that surprising since the share of agricultural growth rate to the overall economic growth in the same year, 2011/12 production year, was lower (2.2 percent) than both the preceding year (4.1 percent) as well as succeeding production year (3.1 percent) (Bachewe *et al.,* 2015). Regarding livestock herd size per annum, sample households in Oromia region have the highest average of 3.1 TLU, followed by sample households in

Amhara and SNNP regions with 2.9 TLU each 2.62 TLU in Tigray. Other inputs including area of land, family labor, and number of traditional plough have more or less similar average values with the national average and across regions as well.



*Note: **O_Land**= Output per hectare of land in ETB, **O_Lab**= Output per adult equivalent family labor in ETB, **O_TLU**= Output per TLU in ETB*

Figure 6. Annual average agricultural output and total variable cost among sample households, by region.

There are few interesting facts to be described based on Figure 6. Even though sample households from Tigray region have the second lowest average value of agricultural outputs, surprisingly, they were found to be the most effective ones in terms of output per hectare of land (average ETB 11,811/ha) and output per TLU (ETB 11,490/TLU). As shown in Figure 6, concerning output per family labor, they have the second highest average value (ETB 2,114/adult equivalent), following the average value from sample households in Amhara (ETB 2,173/adult equivalent). Sample households from Amhara (ETB 9,288/ha of land and ETB 6,992 /TLU) and Oromia (ETB 8,965/ha of land, ETB 2,019/adult equivalent, and ETB 6,070 /TLU) regions comes at the second and third places respectively in terms of annual average values of output per units of inputs. As can be noticed in Figure 6, sample households from the SNNP have the lowest average values of output to units of inputs ratio (ETB 6,040/ha of land, ETB 1,263/adult equivalent, and ETB 2,865 /TLU).

Furthermore, as shown in Table 7, Age and sex of household heads, crop rotation practice, ownership of beehives, and shock prevalence across regions have somehow similar characteristics with the national level data described in the previous sub-section. As shown in Table 7, a significant number of sample farmers (50 percent) received credit whereas twenty to 27 percent of sample farmers have received credit in the other regions. Off-farm activities are practiced by 29, 27, 23, and twenty percent of sample farmers in Oromia, SNNP, Tigray, and Amhara regions. The highest annual mean temperature is recorded in Tigray which is equivalent to 20.1 ºC whereas it is relatively lower in Oromia (18.5 ºC), SNNP (18.4 ºC), and Amhara (17.5) regions where the sample households are located. Moreover, the maximum annual average rainfalls (January through December) is recorded in SNNP, 1054 mm. The average amount of rainfalls recorded in Oromia, Amhara, and Tigray is 850, 799, and 683 respectively.

Table 7. Descriptive Statistics of important variables, by Region.

	Tigray Region			Amhara Region			Oromia region			SNNP Region		
Variables	**NO***	**Mean**	**SD****	**NO***	**Mean**	**SD****	**NO***	**Mean**	**SD****	**NO***	**Mean**	**SD****
Year	447	2.00	0.82	1,047	2.00	0.82	741	2.00	0.82	1,230	2.00	0.82
Ttl_output	447	5409	5873	1,047	6468	6054	741	6200	6633	1,230	3908	4650
TVC	447	717	798	1,047	804	1202	741	695	1071	1,230	472	792
TLU	385	2.62	1.93	1,019	2.89	1.94	718	3.10	2.14	1,184	2.90	1.92
area_land	403	10648	8173	1,001	11740	7755	720	13410	10056	1,214	9116	7330
F_Labor	447	3.15	1.37	1,047	3.17	1.30	741	3.52	1.41	1,230	3.41	1.40
No_tr_plough	447	1.18	0.82	1,047	0.99	0.58	741	0.87	0.67	1,230	0.75	0.63
Age	446	48.36	15.57	1,046	46.05	14.79	740	44.77	15.02	1,230	43.72	13.83
Sex	447	0.26	0.44	1,047	0.17	0.38	741	0.19	0.40	1,230	0.20	0.40
Education	445	0.11	0.38	1,044	0.05	0.24	738	0.30	0.65	1,228	0.29	0.63
Credit_user	450	0.50	0.50	1,048	0.27	0.45	727	0.20	0.40	1,226	0.25	0.43
Shock	447	0.45	0.50	1,047	0.39	0.49	741	0.51	0.50	1,230	0.48	0.50
Off_farm_d	450	0.23	0.42	1,056	0.20	0.40	738	0.29	0.45	1,230	0.28	0.45
Crop_rotation	444	0.94	0.24	1,039	0.93	0.25	728	0.82	0.38	1,226	0.85	0.36
Beehives	447	0.09	0.28	1,047	0.07	0.26	741	0.11	0.31	1,230	0.08	0.27
Agroeco_zone	447	321.85	0.35	1,046	322.54	0.53	741	322.92	0.68	1,229	323.55	0.61
Temp_ann_mean	447	201	36	1,046	175	32	741	185	26	1,229	184	21
RF_avg_ttl	447	683	231	1,046	799	213	741	950	279	1,229	1054	206

*Note: *Number of observation. **Standard Deviation. HH(H)=Household (Head). The labels to variables is presented in table 6.*

8.6 Distribution of sample smallholder farmers across different regions and zones

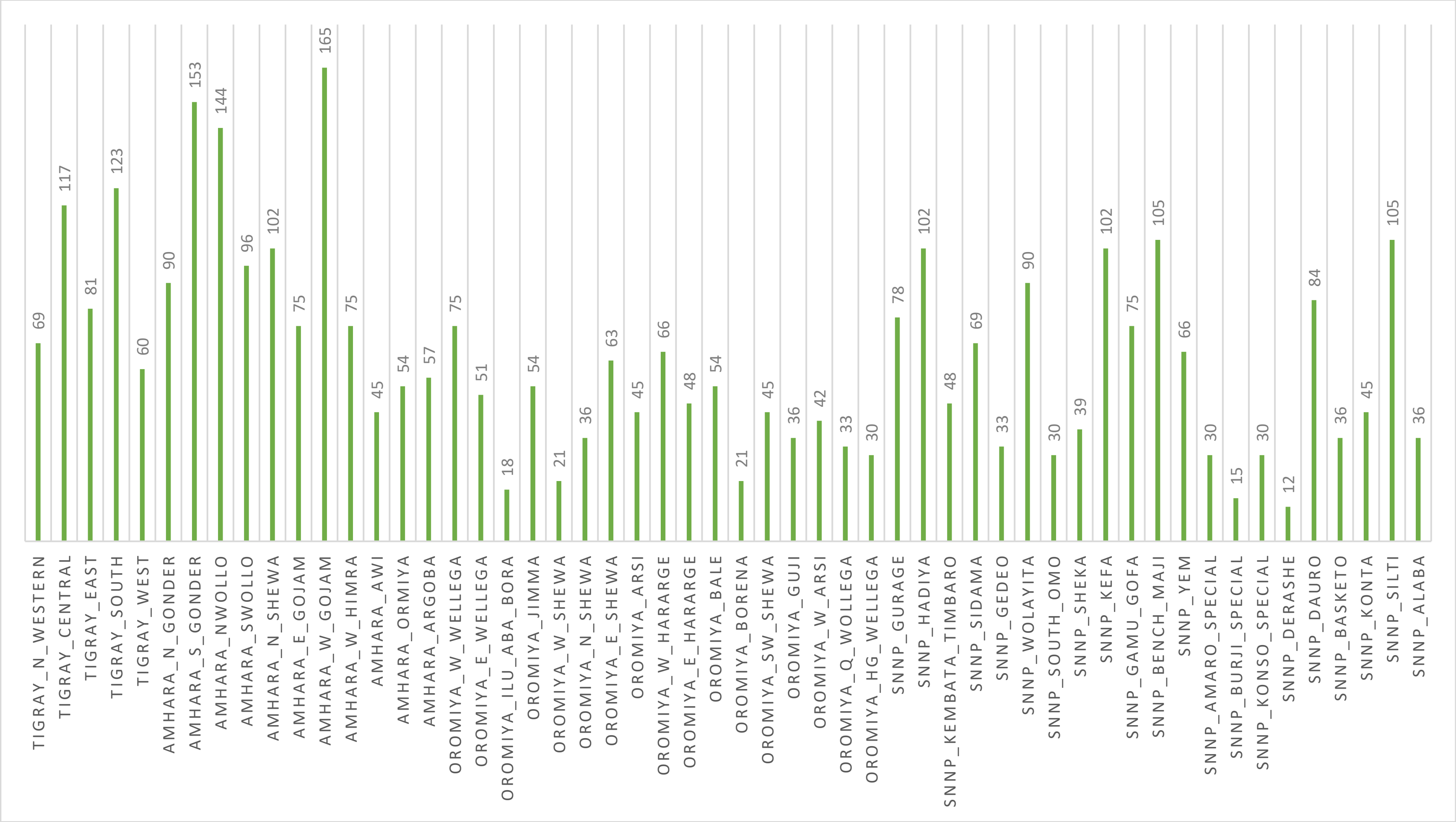


Figure 7. Distribution of number of sample smallholders by Region(i)_Zone(j).

8.7 Determinants of Technical Inefficiency and their Expected Signs

Table 8. *Inefficiency determinants and expected signs.*

Name of the variable	**Labels**	**Expected signs of the determinants of the inefficiency scores**
hhh_sex	A dummy variable: taking 0 if the HHH is male and 1 if female	**(+)** most studies found that female headed households to be less efficient (e.g., Abebe, 2014; Wubeneh and Ehui, 2006).
Ln_Age	Age of the HHH in years	**(+)** Older farmers are expected to be less efficient (see also e.g., Ahmed *et al.* (2014) Alene and Hassan (2003a).
Credit_user	A dummy variable: indicating that whether the HH use credit (1) or not(0)	**(-)** it has been said in the literature that credit and farmers productivity are positively correlated (e.g., Asefa, 2011).
Off_farm_d	A dummy variable: which indicates that the household earned off farm income(1) or not(0) during the year	**(+)** different technical efficiency studies found different signs of relationship between off-farm income and technical efficiency level. In this thesis off-farm income is expected to negatively affect technical efficiency since farmers wouldn't be fully focused on farming (see e.g., Asefa 2011)
Beehives	A dummy variable: the HH own beehives (1) or not(0)	**(-)** since beekeeping is less demanding in terms of inputs use (Pender and Gebremedhin, 2007), e.g., labor, it is hypothesized to be positively associated with level of technical efficiency.
Shock	A dummy variable: negative shock affected the HH, 0 if no and 1 if yes	(+) households who were negatively affected by any kind of shock are more likely to be less efficient. This variable is included because 46 percent of sample farmers reported that they have faced a shock which negatively affected the household.
Crop_rotation	A dummy variable: 1 if the HH practice crop rotation or 0 if not.	**(-)** crop rotation practice is expected to improve productivity (e.g., Ahmed *et al.*, 2014).
Education	A categorical variable with the following groups	In general Education, in terms of number of years of attending school, has been found to be positively related with technical efficiency of farmers (e.g., e.g., Ahmed *et al.*, 2014; Fita *et al.*, 2013; Tirkaso, 2013; Ahmed *et al.*, 2013; and Asefa, 2011). However, after certain level of years of school attendance, wouldn't be relevant since smallholder farming is not an occupation which requires advanced level of knowledge. Due to this reason individuals who are educated at advanced level would be less efficient as they
Primary (5-8)	The household head completed grade 4 - 8	
High school	The household head completed grade 9 - 12	
Above 12	The household head completed education at least at the level of 12 plus	

		have a tendency to be involved in alternative income gaining opportunities.
Year Year 1 Year 2 Year 3	A time-trend variable year = 2011 year = 2013 year = 2015	**(+)** taking the efforts of government and development organizations towards improved agricultural productivity into consideration, it is expected that production would increase from year to year.
Region	A categorical variable indicating which region is each household located in.	Region fixed-effect is used to account for uncontrolled factors which vary across different locations of sample smallholder farmers.
Tigray	The HH is located in Amhara region	
Amhara	The HH is located in Amhara region	
Oromia	The HH is located in Oromia region	
SNNP	The HH is located in SNNP region	

Note: HH(H)=Household (Head).

8.8 Baseline Econometric Analysis

8.8.1 Corrected Ordinary Least Square (COLS) Estimates using Pooled Data

In general, either various distributional assumptions can be made or distribution free approaches can be employed in the estimation of stochastic frontier function parameters and of technical (in)efficiency scores. The first possible estimation approach imposes different specific distributional assumptions (i.e. half normal, truncated normal, exponential and gamma) on the error components and then employ maximum likelihood estimation (MLE) method. The distribution assumption free approach, on the other hand, do not assume specific distribution of the error terms. Examining econometric results based on the distribution free assumption, for example, Corrected Ordinary Least Square (COLS), is an important step. Thus, a pooled data with 3,465 observations is used in this section, and as a result, important production inputs are identified and distribution of residuals is also analyzed.

Following Kumbhakar et at. (2015), model (3) can be rewritten by excluding the statistical error, v_i in order to have the following simple (deterministic) frontier production model.

$$y_i = \beta_0 + \tilde{x}_i'\tilde{\beta} - u_i, \qquad u_i \geq 0,\ i = 1, 2, \dots, N \qquad (16)$$

The COLS approach comprises two steps in order to make sure all observations are bounded by the estimated frontier function, y_i, from the above.

First, the dependent variable, y_i, is regressed over input variables, $\tilde{x}_i$, using OLS method. The OLS estimate gives us a biased intercept but consistent coefficients (Kumbhakar et at., 2015).

As shown in table 9, all input variables are significant at one percent significance level except family labor, which is significant at ten percent. The result indicates that agricultural output elasticity of land, traditional plough, livestock, family labor, and total variable cost is 48, 39.4, 30, thirteen, and eight percent respectively. The positive signs of the coefficients are expected. All variable inputs indicate a production technology close to increasing returns to scale (CRS), i.e. the sum of the coefficients of Ln_TVC (0.081), Ln_TLU (0.289), Ln_Land (0.475) Ln_F_Labor (0.13), and Ln_tr_plough (0.393) is greater than one. Meaning, the value of agricultural output increases by 1.37 percent due to a proportional increase (1 percent each) in utilization of all farm inputs. Moreover, the variance inflation factors (VIF) indicates that there is no multicollinearity problem.

Another key step in stochastic frontier analysis before the more expensive MLE is OLS residuals test. OLS residuals for the production-type stochastic frontier with composed error, $v_i - u_i$, should be negatively skewed (i.e. skewness to the left) since v_i is distributed symmetrically around zero (Kumbhakar et at., 2015 and Tirkaso, 2013). Rejecting the null hypothesis of no skewness means there exists one-sided error. The statistical summary of the residuals indicate that skewness equals to -1.12. The negative sign indicates that the OLS residuals distribution is skewed to the left, which is consistent with production-type stochastic frontier approach.

Figure 8 shows the distribution of OLS resiuals where one can clearly observe the negative skewness (skewness to the left). In addition, the skewness test confirms that the statistic is significant at one percent level of significance – which means the null hypothesis of no skewness in the OLS residuals is rejected. Negative skewness in the production-type stochastic frontier approach indicates the presence of technical inefficiency (Abebe, 2014).

Second, the intercept in the OLS estimator is shifted upward, by the amount of max $\{\hat{e}_i\}$, until all points lie below the estimated frontier production function so that the function lies on the most extreme residual (Heshmati and Mulugeta, 1996 and Kumbhakar et at., 2015). Accordingly, residuals become:

$$\hat{e}_i - max\ \{\hat{e}_i\} = lnY_i - \left\{\left[\hat{\beta}_0 + max\ \{\hat{e}_i\}\right]\tilde{x}_i'\hat{\tilde{\beta}}\right\} \leq 0, \tag{17}$$

and

$$\hat{u}_i \equiv -(\hat{e}_i - max\ \{\hat{e}_i\}) \geq 0, \tag{18}$$

Using $\hat{u}_i$, the estimated technical inefficiency for model (15), the estimator for each smallholder household in the sample is then derived from:

$$\widehat{TE}_i \equiv exp(-\hat{u}_i) \tag{19}$$

Table 9. *OLS estimation of production function using log transformed variables.*

Variables	Labels	OLS	COLS
Estimated Production Function			
Ln_TVC	Total variable cost for agricultural production	0.081*** (0.00737)	
Ln_TLU	Amount of livestock owned in TLU	0.289*** (0.0426)	
Ln_Land	Area of land (Square meters)	0.475*** (0.0237)	
Ln_F_Labor	Family labor based on weights for different age groups	0.130* (0.0677)	
Ln_tr_plough	no of traditional plough owned by the HH	0.393*** (0.0621)	
Constant		2.584*** (0.197)	
Observations		3,200	
R-squared/ Adjusted R-squared		0.307/0.306	
Efficiency Measure			
	Mean Technical Efficiency		0.517

*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

As indicated in Table 9, the estimation result via the COLS approach indicates that mean technical efficiency is close to 52 percent. Thus, on average, sample smallholder farmers produce 52 percent of the maximum potential output in their production. The problem with the COLS approach is that all deviations from the estimated frontier are entirely assumed to be caused by inefficiency and the role of statistical noises or measurement errors is ignored (Kumbhakar *et al.*, 2015). In reality however, random errors (i.e. both measurement errors and statistical noise) are common in any kind of econometric analysis. Now it is reasonable to proceed to a model with parametric distributional assumptions so that MLE is employed for more consistent econometric estimates.

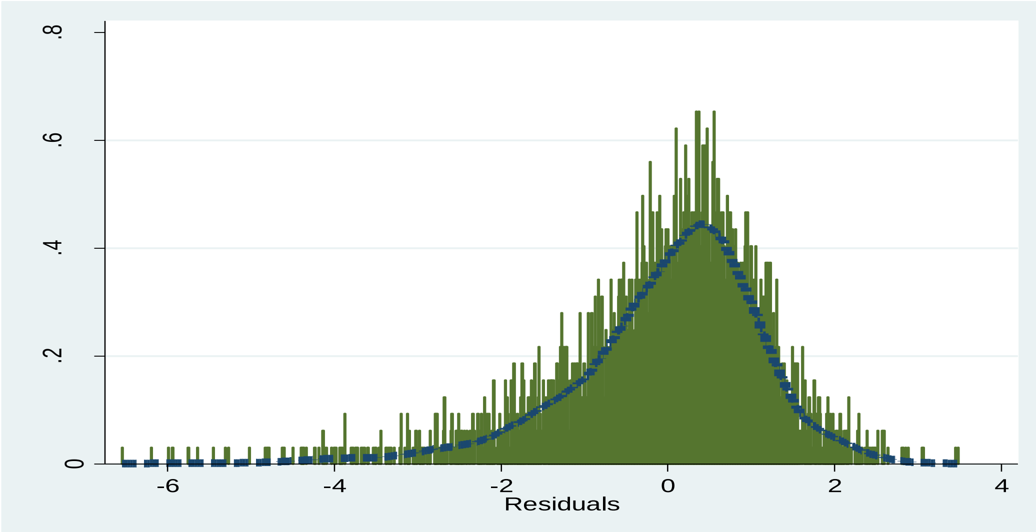


Figure 8. Histogram of OLS residuals.

8.8.2 Cross sectional data Analysis and Choice of Distributional assumption

Before proceeding to the panel data model, the stochastic frontier model is estimated on the three cross-sectional data sets to highlight benchmark properties. The cross-section SF models are utilized in order to have better understanding of the data and get some inputs to the panel data model for better accuracy.

In cross-sectional models, identification of appropriate distributional assumption is an important step. The most common distributional assumptions in stochastic frontier approach are half-normal, truncated normal, exponential, and gamma distributions of the one-sided error (Kumbhakar et at., 2015 and Belotti *et al.*, 2012). Tirkaso (2013) noted the variation of econometric estimates across different distributional assumption is insignificant most of the times. For example, Greene (1990) also found roughly similar estimates of mean inefficiencies with these four different distributional assumptions though the gamma distribution which yielded different efficiency distribution. Putting gamma distribution aside, due to numerical difficulties in the estimation of the model parameters, theoretical justification and statistical results are used to choose one among the other three distributional assumptions. Cross-section model estimation is undertaken for each year using the three distributional assumptions, half normal, truncated normal, and exponential. The model parameters under each of the nine models (model with three distributional assumptions for each of the three years cross-sectional data) are in the same line and the average inefficiency estimates have more or less similar distribution. Many researchers also avoid exponential and half-normal models because their mode is zero, which means significant portions of inefficiency effects are quite close to zero (Coelli *et al.*, 2005). This implies the corresponding technical efficiencies of sample individuals would be in the neighborhood of one – which is not convincing in the case of smallholding farmers whose production is greatly constrained by environmental factors and improved farm inputs. Due to this similar feature of these assumptions, they usually provide similar econometric estimates (Paulsen, 2014). On the other hand, the truncated normal model possesses greater flexibility since it allows a wider range of distributional forms. Note that the objective of cross-section data model analysis is not the primary objective of this thesis, rather the results are used for comparison of parameters and mean efficiency scores over years. In addition, the distributional assumption for the panel data model is a (left-)truncated model as justified in section 3.4. In order to see how econometric estimates behave between the cross-sections and the panel data models, the use of similar distributional assumption, i.e. truncated normal, across different models make more sense.

Table 10. *Cross-section SF models for year 2011, 2013 and 2015 (truncated normal).*

Variables	Labels	Year 2011	Year 2013	Year 2015
Frontier				
Ln_TVC	Total variable cost for agricultural production	0.0301***	0.0515***	0.0745***
		(0.0115)	(0.00774)	(0.0103)
Ln_TLU	Livestock herd size owned in TLU	0.299***	0.188***	0.451***
		(0.0718)	(0.0444)	(0.0562)
Ln_Land	GPS or Rope-and-Compass measured area of land (sqm)	0.304***	0.436***	0.384***
		(0.0367)	(0.0292)	(0.0345)
Ln_F_Labor	Family labor measured in adult equivalent	0.226*	0.00343	0.0981
		(0.117)	(0.0736)	(0.0891)
Ln_tr_plough	No of traditional plough owned by the HH	0.292***	0.353***	0.232***
		(0.108)	(0.0693)	(0.0800)
		(0.273)	(0.126)	(0.170)
sigma_v		5.799*	24.945*	29.937*
		(4.7190)	(20.9960)	(19.5591)
sigma_v		0.6597***	0.487***	0.688***
		(0.0474)	(0.0219)	(0.0305)
lambda		8.790431*	51.205*	43.521*
		(4.6950)	(20.9890)	(19.5597)
Constant		5.051***	4.667***	4.314***
		(0.428)	(0.298)	(0.339)
Estimated Technical Efficiencies				
	Mean	0.4575	0.6035	0.5586
	Min	0.0012	0.0076	0.0019
	Max	0.8510	0.9151	0.8479

*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 10 shows econometric results of stochastic frontier model using cross-sectional data sets from each year with truncated normal distributional assumption. As in the COLS model, all inputs are significant at one percent significance level for all years. The only exception to this is Ln_F_Labor which has positive coefficient with ten percent level of significance in year 2011, positive sign but statistically insignificant in year 2013 and 2015. The ratio δ of the standard error of u_i to the corresponding v_i, λ[28], is greater than one and statistically significant at ten percent in all years. This suggests the one-sided error, u_i, dominated the symmetric error v_i – hence, it confirms the presence of technical inefficiency among the sample households over the three years period of time. The γ[29](gamma) also takes a value of 0.98 in 2011 and 0.99 in each of the other years. This implies that over 98 percent of the variation in the composed error is due to the inefficiency term, u_i in 2011 cross-sectional data model. Both in 2013 and 2015 models, only one percent of the variations are explained by the symmetric error, v_i. The output elasticity of Ln_Land is 0.30, 0.44, and 0.38 in 2011, 2013 and 2015 respectively which is the largest among the inputs. As in the pooled data OLS result, the elasticities of inputs add up greater than one, indicating increasing returns to scale production technology. The average estimated technical efficiencies of sample stallholder farmers is 45.75, 60.35 and

[28] $\lambda\ (lambda) = \frac{\sigma_u}{\sigma_v}$

[29] $\gamma\ (gamma) = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$

(e.g., see Coelli and Battese, 1996 p.107).

55.86 in the first, second and last years. Mekonnen (2013) also found differences in technical efficiency scores across three years, but the variation is not significant as the one found in this thesis. This would not be surprising as if we look at the economic growth trends before and after 2004 since Mekonnen (2013) used a data collected between 1999 and 2004, whereas the data utilized by the current thesis is collected recently, between 2011 and 2015.

Rapid change in agriculture started to be observed since 2004 and continued till recently (Bachewe *et al.*, 2015). Therefore, it is reasonable to expect the yearly variations in recent technical efficiency scores would be higher due to relatively rapid technological or skills improvements coupled with climate variations in recent years. Several agriculture focused bilateral or multilateral development projects have been implemented after 2004. For example, such huge programs as Productive Safety Net Program (PSNP), Agricultural Transformation Agency's projects, Growth and Transformation Plan I and II (GTP I and II), and other related projects/programs have been fully or partially focused on improving smallholders productivity and production (see ATA, 2018; NBE, 2017; WB, 2017; and MoFED, 2006). As a result, it has been reported that agriculture has been the fastest growing sector and the major driving force to economic growth averaged 10.5 percent between 2003/4 through 2015/16 (see World Bank, 2017). Besides all of this, environmental shocks also affected smallholders' production (e.g., see Abduselam, 2017b; USAID Feed The Future, 2016; and Tull, 2017). Given these enormous development efforts in agriculture and environmental shocks occurred in the last decade, it would not be rational not to anticipate such unexaggerated deviations during the period under study, namely 2011-2015. In general, this gives us some insights about how the data for the same sample behaves over years. For example, an important indication from the cross-section SF models is inclusion of time dummies (year) and other important factors will be important to capture unforeseen heterogeneities for more precise econometric estimates

8.9 Distribution of estimated technical efficiency scores

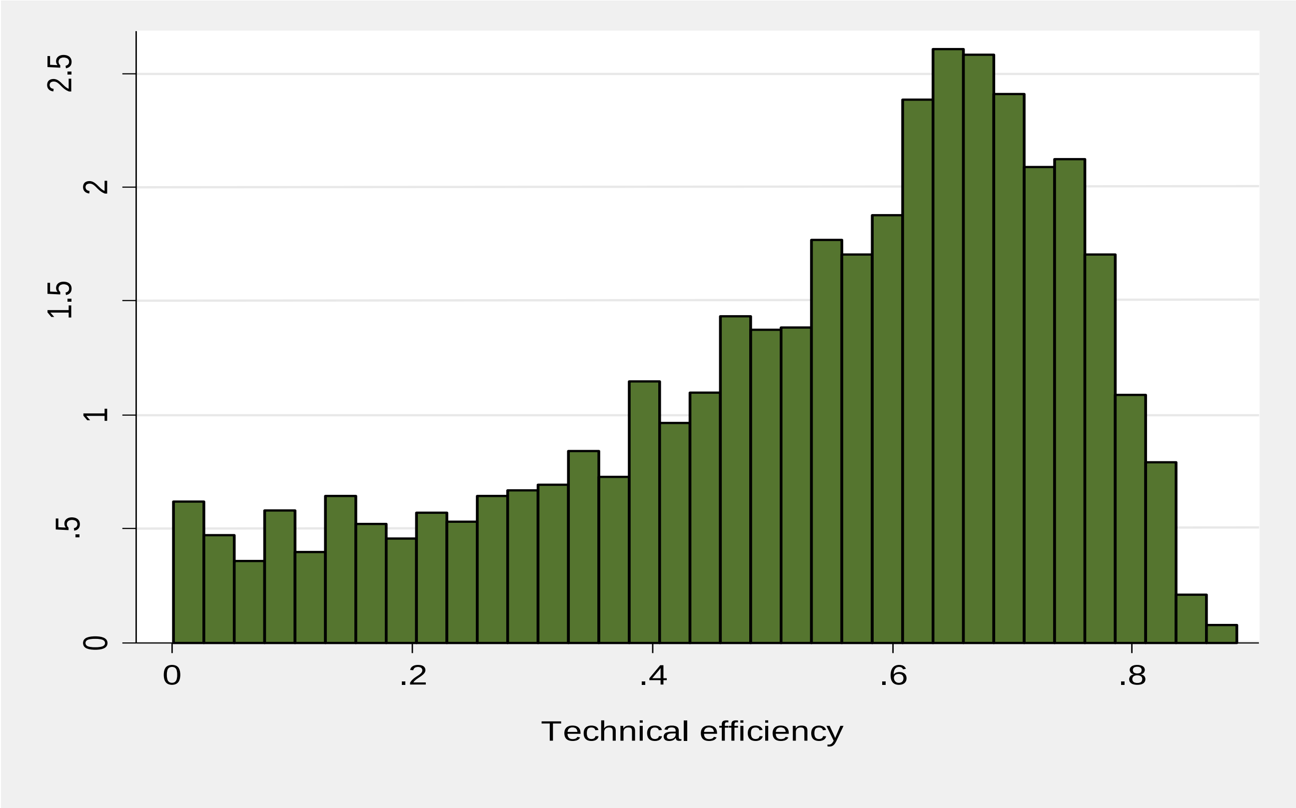


Figure 9. Distribution of estimated technical efficiency scores.

8.10 Distribution of Technical efficiency scores across different regions and zones

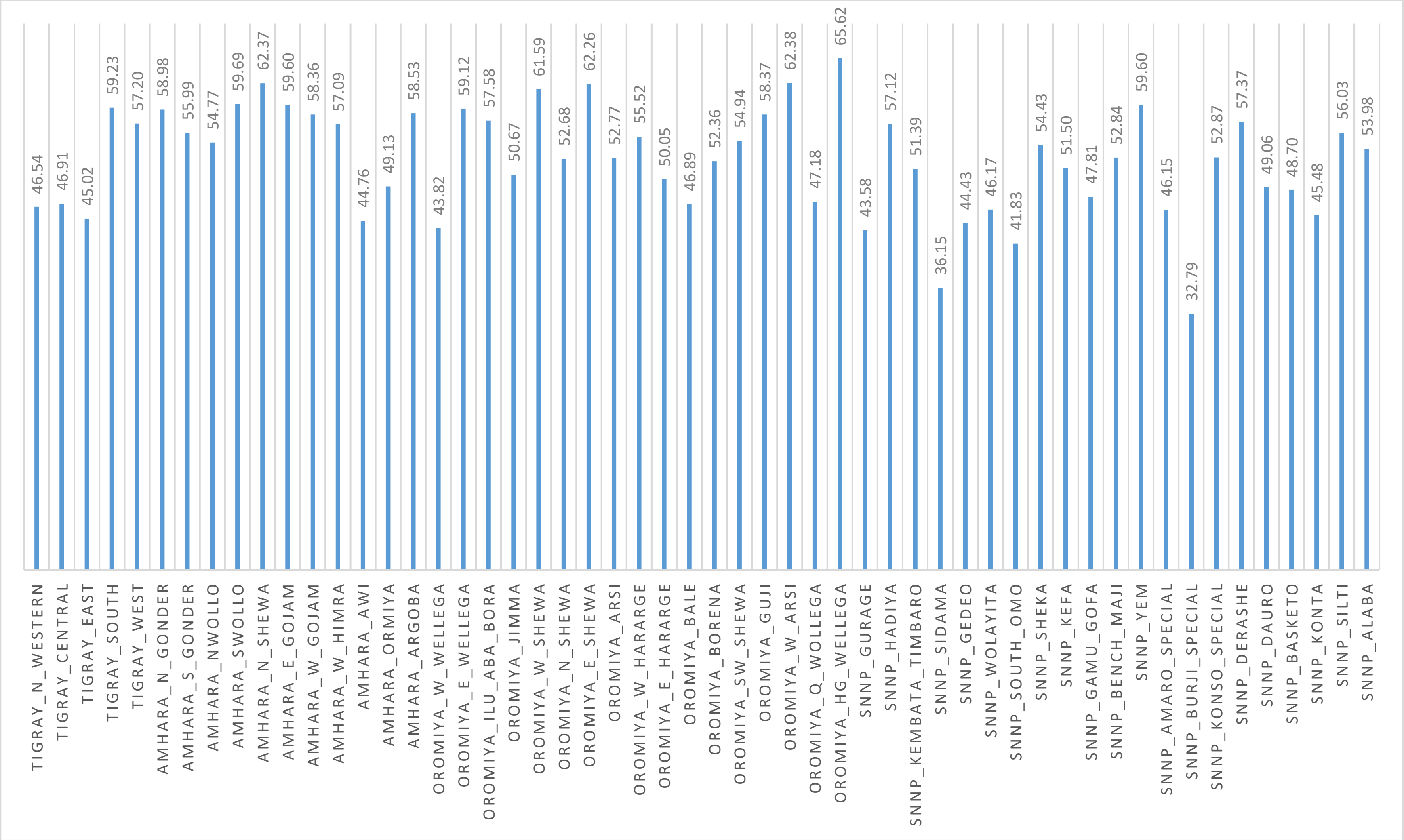


Figure 10. Distribution of predicted technical efficiency scores (in percent) by Region(i)_Zone(j).

8.11 Regression result of the inefficiency model

Table 11. *MLE for inefficiency determinants – inefficiency term is the dependent variable.*

Variables	**Labels**	**Coefficients**	**Standard error**
hhh_sex	*0 if the HHH is male and 1 if female*	0.0268***	0.00998
Age	*Age of the HHH in years*	0.0196	0.0131
Credit_user	*whether the HH use credit (1) or not(0)*	-0.0430***	0.00841
Off_farm_d	*The household earned off farm income(1) or not(0) during the year*	0.00599	0.00889
Beehives	*The HH own beehives (1) or not(0)*	-0.0354***	0.0128
Shock	*negative shock affected the HH, 0 if no and 1 if yes*	0.0263***	0.00738
Crop_rotation	*1 if the HH practice crop rotation or 0 if not*	-0.0433***	0.0116
Education			
Primary (5-8)	*The household head completed grade 4 - 8*	-0.0178	0.0119
High school	*The household head completed grade 9 - 12*	-0.0289	0.0316
Above 12	*The household head completed education at least at the level of 12+*	0.0509*	0.0309
Year[30]			
Year 2	*year = 2013*	-0.0543***	0.00853
Year 3	*year = 2015*	-0.0352***	0.00841
Region[31]			
Amhara	*The HH is located in Amhara region*	-0.0652***	0.0139
Oromia	*The HH is located in Oromia region*	-0.0459***	0.0148
SNNP	*The HH is located in SNNP region*	0.000140	0.0137
Constant		0.491***	0.0534
Observations		3,181	

*Note: *** p<0.01, ** p<0.05, * p<0.1. HH(H)=Household (Head).*

[30] Year 1 (2013) is used as a reference to the next two years, hence it is omitted.
[31] Tigray region is omitted in the regression result since it is used as the reference region.

9. References

Abebe, G.G., 2014. *Off-farm income and technical efficiency of smallholder farmers in Ethiopia—a stochastic frontier analysis*. European Erasmus Mundus Master Program: Agricultural Food and Environmental Policy Analysis (AFEPA). Degree thesis, (862).

AGP, 2018. *Background of Agricultural Growth Program (AGP).* [Online] Available at: <http://ethioagp.org/background/> [Accessed 19 March 2018].

Ahmed, B., Haji, J. and Geta, E., 2013. *Analysis of farm households' technical efficiency in production of smallholder farmers: The case of Girawa District, Ethiopia.* Am.-Eur. J. Agric. Environ. Sci, 13(12), pp.1615-1621.

Ahmed, M.H., 2014. *Technical efficiency of maize producing farmers in Arsi Negelle, central rift valley of Ethiopia: stochastic frontier approach.* Agriculture and Forestry/Poljoprivreda i Sumarstvo, 60(1).

Alauddin, M. and Tisdell, C., 1988. *Patterns and determinants of adoption of high yielding varieties: farm-level evidence from Bangladesh.* The Pakistan Development Review, pp.183-210.

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

Alene, A.D. and Hassan, R.M., 2003b, August. *Measuring the impact of Ethiopia's new extension program on the productive efficiency of farmers.* In Proceedings of the 25th International Conference of Agricultural Economists (IAAE) (Vol. 16, p. 22).

Alene, A.D. and 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), p.5.

Alene, A.D., Manyong, V.M. and Gockowski, J., 2006. *The production efficiency of intercropping annual and perennial crops in southern Ethiopia: A comparison of distance functions and production frontiers.* Agricultural systems, 91(1-2), pp.51-70.

Amede, T., Auricht, C., Boffa, J.M., Dixon, J., Mallawaarachchi, T., Rukuni, M. and Teklewold-Deneke, T., 2017. *A farming system framework for investment planning and priority setting in Ethiopia*. Australian Centre for International Agricultural Research (ACIAR).

Asante, B.O., Villano, R.A. and Battese, G.E., 2017. *Integrated crop-livestock management practices, technical efficiency and technology ratios in extensive small-ruminant systems in Ghana.* Livestock Science, 201, pp.58-69.

Asefa, S., 2011. *Analysis of technical efficiency of crop producing smallholder farmers in Tigray, Ethiopia*.

ATA, 2018. *The ATA's Role within the Transformation Agenda.* [Online] Available at: <http://www.ata.gov.et/about-ata/atas-role/> [Accessed 19 March 2018].

Bachewe, F. N., Berhane, G., Minten, B., and Taffesse, A. S. (2015). *Agricultural growth in Ethiopia (2004–2014): Evidence and drivers.* International Food Policy—Ethiopia Strategy Support Program Working Paper, 81.

Bagi, F.S. and Huang, C.J., 1983. *Estimating production technical efficiency for individual farms in Tennessee.* Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 31(2), pp.249-256.

Barham, J., and Chitemi, C. (2009). *Collective action initiatives to improve marketing performance: Lessons from farmer groups in Tanzania.* Food policy, 34(1), 53-59.

Battese, G.E. and Coelli, T.J., 1992. *Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India.* Journal of productivity analysis, 3(1-2), pp.153-169.

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

Bayne, N., 2017. *Staying together: the G8 summit confronts the 21st century.* Routledge.

Belotti, F., Daidone, S., Ilardi, G. and Atella, V., 2012. *Stochastic frontier analysis using Stata.*

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

Bravo-Ureta, B.E., Solís, D., López, V.H.M., Maripani, J.F., Thiam, A. and Rivas, T., 2007. *Technical efficiency in farming: a meta-regression analysis.* Journal of productivity Analysis, 27(1), pp.57-72.

Cabrera, V.E., Solis, D. and Del Corral, J., 2010. *Determinants of technical efficiency among dairy farms in Wisconsin.* Journal of dairy science, 93(1), pp.387-393.

Cabrera, V.E., Solis, D. and Del Corral, J., 2010. *Determinants of technical efficiency among dairy farms in Wisconsin.* Journal of dairy science, 93(1), pp.387-393.

Coelli, T.J. and Battese, G.E., 1996. *Identification of factors which influence the technical inefficiency of Indian farmers.* Australian Journal of Agricultural Economics, 40(2), pp.103-128.

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

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J. and Battese, G.E., 2005. *An introduction to efficiency and productivity analysis.* Springer Science and Business Media.

Collier, P. and Dercon, S., 2014. *African agriculture in 50 years: smallholders in a rapidly changing world?.* World development, 63, pp.92-101.

Croppenstedt, A. and Demeke, M., 1997. *An empirical study of cereal crop production and technical efficiency of private farmers in Ethiopia: a mixed fixed-random coefficients approach.* Applied Economics, 29(9), pp.1217-1226.

CSA and WB, 2013. *Ethiopian Socioeconomic Survey (ERSS) Survey Report.* [Online] Available at: <http://siteresources.worldbank.org/INTLSMS/Resources> [Accessed 18 April 2018].

CSA and WB, 2017. *Ethiopia Socioeconomic Survey (ESS) Wave Three (2015/2016). Basic Information Document.* [Online] Available at: <http://microdata.worldbank.org/index.php/home> [Accessed 03 July 2018].

CSA, 2017. *Report on area and production of major crops (Private peasant holdings, Meher season).* [Online] Available at: <http://www.csa.gov.et/index.php/ehioinfo-internal?download=771:report-on-area-and-production-of-major-crops-2009-e-c-meher-season> [Accessed 19 April 2018].

CSA, 2017. *Report on livestock and livestock characteristics (Private peasant holdings, Meher season).* [Online] Available at: <http://www.csa.gov.et> [Accessed 19 April 2018].

Dahlin, S. and Rusinamhodzi, L., 2014. *Review of interventions and technologies for sustainable intensification of smallholder crop production in sub-humid sub-Saharan Africa* (No. 2014: 5).

Demeke, A.B., Keil, A. and Zeller, M., 2011. *Using panel data to estimate the effect of rainfalls shocks on smallholders food security and vulnerability in rural Ethiopia.* Climatic change, 108(1-2), pp.185-206.

Dethier, J.J. and Effenberger, A., 2012. *Agriculture and development: A brief review of the literature.* Economic Systems, 36(2), pp.175-205.

Diao, X., Hazell, P. B., Resnick, D., and Thurlow, J. (2007). *The role of agriculture in development: Implications for Sub-Saharan Africa (Vol. 153).* Intl Food Policy Res Inst.

FAO, 2018. Africa Sustainable Livestock (ASL) 2050. *Livestock and livelihoods Livestock and livelihoods spotlight Cattle sector ETHIOPIA.* [Online] Available at: <http://www.fao.org/3/i8676en/I8676EN.pdf> [Accessed 14 July 2018].

Fita, L., Trivedi, M.M., Patel, A.M., Tassew, B. and Joshi, C.G., 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).

Fletschner, D.K. and Zepeda, L., 2002. Efficiency of small landholders in Eastern Paraguay. *Journal of Agricultural and Resource Economics*, pp.554-572.

Haji, J. and Andersson, H., 2006. *Determinants of efficiency of vegetable production in smallholder farms: The case of Ethiopia.* Acta Agriculturae Scand Section C, 3(3-4), pp.125-137.

Hansson, H. and Öhlmér, B., 2008. *The effect of operational managerial practices on economic, technical and allocative efficiency at Swedish dairy farms.* Livestock Science, 118(1-2), pp.34-43.

Hardaker, J.B. and Fleming, E.M., 1989. *Agricultural research problems in small developing countries: Case studies from the South Pacific Island Nations.* Agricultural Economics, 3(4), pp.279-292.

Heady, E.O., HAROLDSEN, E.O., MAYER, L.V. and TWEETEN, L.G., 1965. *Roots of the Farm Problem: Changing Technology, Changing Capital Use, Changing Labor Needs.*[By] Earl O. Heady, Edwin O. Haroldsen, Leo V. Mayer, Luther G. Tweeten. Iowa State University Center for Agricultural and Economic Development, Iowa State University Press.

Heshmati, A. and Mulugeta, Y., 1996. *Technical efficiency of the Ugandan matoke farms.* Applied Economics Letters, 3(7), pp.491-494.

Hirschman, A.O., 1958. *The strategy of economic development (No. 04; HD82, H5.).*

Huang, W., Bruemmer, B. and Huntsinger, L., 2017. *Technical efficiency and the impact of grassland use right leasing on livestock grazing on the Qinghai-Tibetan Plateau.* Land Use Policy, 64, pp.342-352.

Hunter, W.C. and Timme, S.G., 1991. *Some evidence on the impact of quasi-fixed inputs on bank scale economy estimates.* Economic Review-Federal Reserve Bank of Atlanta, 76(3), p.12.

Hurni, H., 1998. Agroecological belts of Ethiopia: explanatory notes on three maps at a scale of 1: 1,000,000. *Soil conservation research program of Ethiopia, Addis Ababa, Ethiopia*, *31*.

Kokkinou, A., 2010. A Note on Theory of Productive Efficiency and Stochastic Frontier Models. *European Research Studies*, *13*(4), p.109.

Komicha, H.H. and Öhlmer, B., 2006. *Effect of credit constraint on production Efficiency Of farm households in Southeastern Ethiopia.* Ethiopian Journal of Economics, 15(1), pp.1-33.

Kumbhakar, S.C., Wang, H. and Horncastle, A.P., 2015. *A practitioner's guide to stochastic frontier analysis using Stata.* Cambridge University Press.

Kuznets, S. and Murphy, J.T., 1966. *Modern economic growth: Rate, structure, and spread (Vol. 2).* New Haven: Yale University Press.

Latruffe*, L., Balcombe, K., Davidova, S. and Zawalinska, K., 2004. *Determinants of technical efficiency of crop and livestock farms in Poland.* Applied economics, 36(12), pp.1255-1263.

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

Makombe, G., Namara, R.E., Awulachew, S.B., Hagos, F., Ayana, M. and Kanjere, M., 2017. *An analysis of the productivity and technical efficiency of smallholder irrigation in Ethiopia.* Water SA, 43(1), pp.48-57.

Mekonnen, D.K., 2013. *Three essays on productivity, efficiency, and the role of social networks* (Doctoral dissertation, University of Georgia).

Mellor, J.W., 1976. *New economics of growth.* Cornell University Press.

MoFED, 2002. *Sustainable Development and Poverty Reduction Program (SDPRP).* [Online] Available at: <http://siteresources.worldbank.org/INTETHIOPIA/Overview/20207639/2002_07_prsp.pdf> [Accessed 21 June 2018].

MoFED, 2006. *A Plan for Accelerated and Sustained Development to End Poverty (PASDEP).* [Online] Available at: <https://www.afdb.org/en/documents/document/> [Accessed 21 June 2018].

MoFED, 2014. *Growth and Transformation Plan Annual Progress Report for F.Y. 2012/13.* [Online] Available at: <http://www.mofed.gov.et/web/guest/resources-by-category> [Accessed 21 June 2018].

Mohamed, A.A., 2017. *Food security situation in Ethiopia: a review study.* Int J Health Econ Policy, 2(3), pp.86-96.

Murillo-Zamorano, L.R., 2004. *Economic efficiency and frontier techniques.* Journal of Economic surveys, 18(1), pp.33-77.

National Bank of Ethiopia (NBE), 2017. *2016/2017 Annual Report.* [Online] Available at: <https://www.nbe.gov.et/publications/annualreport.html> [Accessed 21 June 2018].

Negassa, A. and Jabbar, M., 2008. *Livestock ownership, commercial off-take rates and their determinants in Ethiopia.* ILRI (aka ILCA and ILRAD).

Ogada, M.J., Muchai, D., Mwabu, G. and Mathenge, M., 2014. *Technical efficiency of Kenya's smallholder food crop farmers: do environmental factors matter?.* Environment, development and sustainability, 16(5), pp.1065-1076.

Olagunju, F.I. and Adeyemo, R., 2007. *Agricultural credit and production efficiency of small scale farmers in south-eastern Nigeria.* Agricultural Journal, 2(3), pp.426-433.

Paulsen, M.B. ed., 2014. *Higher education: Handbook of theory and research (Vol. 31)*. Springer.

Pender, J. and Gebremedhin, B., 2007. *Determinants of agricultural and land management practices and impacts on crop production and household income in the highlands of Tigray, Ethiopia.* Journal of African Economies, 17(3), pp.395-450.

Rae, A.N. and Hertel, T.W., 2000. *Future developments in global livestock and grains markets: the impacts of livestock productivity convergence in Asia-Pacific.* Australian Journal of Agricultural and Resource Economics, 44(3), pp.393-422.

Rezitis, A.N., Tsiboukas, K. and Tsoukalas, S., 2002. *Measuring technical efficiency in the Greek agricultural sector.* Applied economics, 34(11), pp.1345-1357.

SA, A.N., Rashid, S., Gebremedhin, B. and Kennedy, A., 2012. *Livestock Production and Marketing. Food and agriculture in Ethiopia:* Progress and policy challenges, 74, p.159.

Salami, A., Kamara, A.B. and Brixiova, Z., 2010. *Smallholder agriculture in East Africa: Trends, constraints and opportunities.* Tunis: African Development Bank.

Schmidt, P. and Sickles, R.C., 1984. *Production frontiers and panel data.* Journal of Business and Economic Statistics, 2(4), pp.367-374.

Seyoum, E.T., Battese, G.E. and Fleming, E.M., 1998. *Technical efficiency and productivity of maize producers in eastern Ethiopia: a study of farmers within and outside the Sasakawa-Global 2000 project.* Agricultural economics, 19(3), pp.341-348.

Sharp, K., Brown, T. and Teshome, A., 2006. *Targeting Ethiopia's Productive Safety Net Programme (PSNP).* London and Bristol, UK: Overseas Development Institute and the IDL Group.

Sherlund, S.M., Barrett, C.B. and Adesina, A.A., 2002. *Smallholder technical efficiency controlling for environmental production conditions.* Journal of development economics, 69(1), pp.85-101.

Solomon, A. and Authority, E.L.M., 2003. *Livestock marketing in Ethiopia: a review of structure, performance, and development initiatives (Vol. 52).* ILRI (aka ILCA and ILRAD).

Thiam, A., Bravo-Ureta, B.E. and Rivas, T.E., 2001. *Technical efficiency in developing country agriculture: a meta-analysis.* Agricultural economics, 25(2-3), pp.235-243.

Thorpe, W., and Duncan, A., 2012. *Fodder and feed in livestock value chains in Ethiopia: Final report of the Ethiopian Livestock Feeds project*. International Livestock Research Institute (ILRI).

Timmer, C. Peter and Selvin Akkus, 2008. *'The Structural Transformation as a Pathway out of Poverty: Analytics, Empirics and Politics'.* Working Paper Number 150, Center for Global Development.

Timmer, C.P., 2002. *Agriculture and economic development.* Handbook of agricultural economics, 2, pp.1487-1546.

Tirkaso, W.T., 2013. *The role of agricultural commercialization for smallholders productivity and food security.* Thesis presented to Department of Economics, Swedish University of Agricultural Sciences, Sweden.

Tull, K., 2017. *Humanitarian interventions for food/nutrition support in Ethiopia.* [Online] Available at: <https://opendocs.ids.ac.uk/opendocs/handle/123456789/13490> [Accessed 15 March 2018].

U.S. Department of Agriculture (USDA), 2013. *Grain and Feed Annual Report - GAIN Report Number: ET-1301.* [Online] Available at: <https://gain.fas.usda.gov/Recent percent20GAIN percent20Publications> [Accessed 19 April 2018].

USAID Feed The Future (2016). *2016 PROGRESS REPORT: Growing Prosperity for a Food-Secure Future.* [Online] Available at: <https://www.usaid.gov/what-we-do/agriculture-and-food-security/increasing-food-security-through-feed-future> [Accessed 19 March 2018].

Valdés, A. and Foster, W., 2010. *Reflections on the role of agriculture in pro-poor growth.* World Development, 38(10), pp.1362-1374.

Valdés, A. and Foster, W., 2010. *Reflections on the role of agriculture in pro-poor growth.* World Development, 38(10), pp.1362-1374.

WFP, 2012. *Productive Safety Net Programme (PSNP) facts.* [Online] Available at: <https://www.wfp.org/sites/default/files/PSNP percent20Factsheet.pdf> [Accessed 19 March 2018].

World Bank (WB), 2017. *World Bank group County Partnership Framework for the Democratic Republic of Ethiopia 2018-2022.* [Online] Available at: <https://openknowledge.worldbank.org/handle/10986/28389> [Accessed 21 June 2018].

World Bank, 2007. *World Development Report 2008: Agriculture for Development.* World Bank/Oxford University Press, Washington, DC/Oxford.

World Food Program (WFP), 2018. *Country Brief, Ethiopia.* [Online] Available at: <http://www1.wfp.org/countries/ethiopia> [Accessed 21 June 2018].

Wrigley, E.A., 1988. *The limits to growth: Malthus and the classical economists.* Population and Development Review, 14, pp.30-48.

Wubeneh, N. and Ehui, S., 2006, August. *Technical efficiency of smallholder dairy farmers in the central ethiopian highlands.* In Poster paper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia.

Yu, C., 1998. *The effects of exogenous variables in efficiency measurement—a Monte Carlo study.* European Journal of Operational Research, 105(3), pp.569-580.