Mekelle University

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Environmental-Technology Gap and Technical efficiency Estimates of Farm households in Northern Ethiopia (Metafrontier Analysis)

By:

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Declaration

I, **Abrha Megos,** do hereby declare that the thesis entitled ***"Environmental Technology Gap and Technical Efficiency Estimates of farm Households in Tigray Region (Northern Ethiopia); Metafrontier Analysis",*** submitted by me in partial fulfillment of the requirements for the award of Master of Science in Economics (Development Policy Analysis) of Mekelle University, Tigray, is original work and it has not been presented for the award of any other degree, diploma, fellowship or other similar titles, of any other University or Institution.

Abrha Megos Meressa

Signature: _____

Date: _____

Place: Mekelle, Tigray, Ethiopia

Certificate

This is to certify that this thesis entitled "Environmental Technology Gap and Technical Efficiency Estimates of farm Households in Tigray Region (Northern Ethiopia); Metafrontier Analysis" submitted in partial fulfillment of the requirements for the award of the degree of MSc., in Development Policy Analysis to the College of Business and Economics, Mekelle University, through the Department of Economics, done by Mr. **Abrha Megos Meressa**, ID.No. **FBE/PR092/04** is an authentic work carried out by him under my guidance. The matter embodied in this thesis has not been submitted earlier for award of any degree or diploma to the best of my knowledge and belief.

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ABSTRACT

Agriculture is the driving force of the economy in less developed countries like Ethiopia. Consequently, Agricultural productivity demonstrate crucial role for improving the welfare of the vast majority of poor (Sahn et al,. 1997; World bank, 2000) countries. Farm productions in Tigray region (northern Ethiopia) operated in spatially diverse physical environments that are largely beyond the control of farmers. Following the rejection of the null hypothesis that stated there is hemogenious technology across the three geographic locations, this study decompose total factor productivity into technical efficiency and production environment (technology gap) effects among the three groups using stochastic metafrontier analysis.

In this study it is found low mean technical efficiency scores 32.2%, 63.8% and 48.5% for Raya Azebo, Qolla Temben and Saesie Tsaeda Emba districts respectively. Moreover, the mean technical efficiencies relative to their respective metafrontier are far lower than technical efficiency relative the group frontiers implying that there is significant technological gap ratio (TGR). The values of mean TGR scores for the three groups are 54.2%, 57.1% and 21% respectively. The existence of low technical efficiency indicates there is a potential to increase output without increasing inputs applied for agriculture if efficiency problems are solved aptly. Socioeconomic, demographic and farm level factors are found correlated with technical inefficiency of farm households in the area. Some are access to extension service, crop diversification, age of the household head etc.

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Finally, for any errors or inadequacies that may remain in this work, of course, is entirely my own responsibility.

Abrha Megos

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Table of Contents

Contents **Page**

List of Tables

Table **page**

List of figures

ACRONYMS

ADLI	Agricultural Development Led Industrialization
CIA	Central intelligence Autherity
CSA	Central Statistical Authority
DEA	Data envelopment analysis
DMUs	Decision making units
EMTR	Environmental metatechnology ratio
FTF	Feed the future
GDP	Gross Domestic Product
HARITA	Horn of Africa risk transfer adaptation
IID	Identically and independently distributed
IMF	International Monetary Fund
Kg	Kilo gram
LR	Likelihood ratio
MLE	Maximum Likelihood Estimate
MoARD	Ministry of Agriculture and Rural Development
MEDaC	Ministry of Economic Development and Cooperation (MEDaC)
NBE	National bank of Ethiopia
SFM	Stochastic Frontier Model
SMF	Stochastic Metafrontier
SSA	Sub-Saharan Africa
TE	Technical efficiency from stochastic frontier
TE*	Technical efficiency from metafrontier
TGR	Technology gap ratio

List of the Appendix

Appendix **Page**

CHAPTER ONE

INTRODUCTION

1.1Background of the study

Agriculture plays a leading role in the economies of many developing countries, especially in sub Saharan Africa (SSA) including Ethiopia. Its estimated human population of 85 million, which grows annually at about 2.7 percent, put Ethiopia to be the second most populous country in SSA next to Nigeria (Tilahun, 2011). In terms of the country's economy structure, agriculture accounts for roughly 43 to 50 percent of country's gross domestic product, up to 90 % of exports, 83.9 % of labor employment (FTF, 2010). It is also major supplier of food to the domestic consumption in the country. An abundant water resource, diversified agro-ecology (Dega, Weyna-Dega & Kolla), cheap labor force and huge livestock resource characterizes Ethiopian agriculture sector (NBE, 2009; Davis et al., 2010 and Hurni, 1998 cited in Amare, 2011). The existent of such plenty resource endowments made investment in the sector profitable. However, as it has been repeatedly stated in many studies, Ethiopian agriculture manly depends on highly variable rainfall, both in terms of seasonal variation and annual fluctuation, which severely affects the sector's productivity.

Despite great importance of agriculture to Ethiopian economy in terms of GDP, employment and foreign exchange earnings, its productivity has remained low. It is dominated by smallholders, who cultivate 95 percent of the total area under crop production and contribute more than 90 percent of the total agricultural output (MEDaC, 1999 as Cited in Tsegaye et al, 2010). These smallholder farmers have limited access to services such as extension credit, market information and transport services (World Bank, 2010). All these are expected to undermine smallholder famers' bargaining power. This in turn forced them to experience high transport and input costs associated with using commercially supplied inputs such as improved seeds and inorganic fertilizer. Eventually, these factors will force small scale farmers to organize their production less efficiently (less productively) and will make them vulnerable to external shocks, which are outside their control (World Bank, 2010).

A sustainable growth of agriculture productivity is a key element in promotion of sustainable economic progress in developing countries, like Ethiopia, as the sector unarguably is the major driving force in process of raising per capita income of the country. It translates to the country's ability to feed its ever-increasing population, to alleviate its poverty and to enhance its food security. Given high level of poverty in the agriculture sector, improving farmers' productivity is a policy imperative rather than a choice. Farmers can increase productivity not only by improving efficiency alone, but also by technical change or the exploitation of scale economies or from some combination of these three techniques. The developments of yield-enhancing technologies that are appropriate to the country's resource endowments, socioeconomic conditions and biophysical environment are critically needed for sustainable development of the country. The technologies backed-up with the agricultural extension service are expected of improving the technical efficiency (TE) of farmers and thereby will end up raising the welfare of rural population (economies). However, in Ethiopia despite immense agricultural potential, the capacity of the sector to meet the domestic and export demand has been handicapped by low productivity (Tsegaye and Berg, 2010 and Mulat et al., 2004). Extreme rainfall dependency, weather instability, poor soil fertility, animal and plant diseases, highly fragmented farmlands, environmental degradation (Aberra, 2010) coupled with limited accesses and use of agricultural technologies, inefficient utilization of scarce resources and technologies (Assefa, 1995) are factors contributing for its poor performance of agricultural sector.

In a dynamic environment, it is argued that farmers encounter considerable inefficiencies before the realization of the intended gains from technological change (Ali and Chaudhry, 1990; Ali and Byerlee, 1991 and Xu and Jeffrey, 1998). In other words, there is a time lag between farmers' adoption of a new technology and achieving efficient use of that technology. Knowledge of the extent and causes of such inefficiencies among adopters of improved technology will guide policy makers in their effort to increase agricultural production by designing more effective and efficient institutional support services. In an effort to raise agricultural production and productivity, policy makers in developing countries have placed substantial emphasis on new production technologies that are expected to be adopted by farmers (Arega and Zeller, 2006). From the time when improvements in productivity are theoretically attributed to improvement in technical efficiency and to improvement in technological progress (Färe et al. 1994), several

studies have focused on the role of efficiency in the improving of agricultural productivity. In particular developing economies like Ethiopia where resources are meager and capacity for developing and adopting new technologies are limited, building efficient utilization capacity of existing technologies is the most viable option to increasing productivity (Khuda, 2007; Oyeranti, 2000 and Fekadu, 2004).

Differences in resource endowments both within and between locations are expected to influence the technologies applied in agriculture and cause location-specific effects on production and technical change. Total factor productivity in agriculture can be increased either by improving technical efficiency (TE) or by improving level of technology used or both. A relevant question for agricultural policymakers is whether to pursue a strategy directed towards technological change or a strategy towards efficiency change (Nkamleu, 2004) or both. The presence of shortfalls in production efficiency means that output can be increased without requiring additional conventional inputs and without the need for new technology. If this is the case, then empirical measures of efficiency are necessary in order to determine the magnitude of the gain that could be obtained by minimizing the inefficiencies. In the presence of technological gap ratio (TGR), technical progress is the appropriate strategy to significantly increase agricultural production. Production technologies could differ across locations since producers can apply different combination of inputs in their production due to difference in their environmental, household level, socio-economic and institutional characteristics. With this setting, this paper will extend the existing literature by considering if producers face location and farm-specific production frontiers.

1.2 Statement of the problem

There is a consensus among economists that resources and capital endowments differ between locations and farmers (Hockmann, 2012 and Mariano et al., 2011). Farmers in different locations, regions and/or countries face different production opportunities. Technically, they make choices from different sets of feasible input–output combinations. These so-called technology sets differ because of differences in available stocks of physical, human and financial capital (e.g., type of machinery, size and quality of the labor force, access to foreign exchange and soon), economic infrastructure (e.g., number of ports, access to markets and soon), resource

endowments (e.g., quality of soils, climate, energy resources and soon) and any other characteristics of their physical, social and economic environment in which production taken place. Such differences made efficiency estimates better fitted if estimated using separate production frontiers for different groups of decision making units (DMUs). And knowing this fact, it is better to start from the hypothesis that the technologies may differ between farmers operating under different agro-climatic conditions. But when only continental, country or regional data are available, we have to make a critical assumption that production (technical) possibilities of farmers in different locations can be described by the same production function (Coelli et al, 2005) though it is unlikely even if the functional form is flexible. Given this assumption a joint production frontier technology for all farms (DMUs) will be defined, and deviations from the frontier could be called as technical inefficiency estimates (Aigner et al, 1977; Pitt and Lee, 1981; Admassie and Heidhues, 1996; Hailu et al, 1998 and etc). However, in this case the term should not be interpreted only as managerial inefficiency but as a relative productivity difference related to resource endowments embodied; it could be environmental, capital or human (managerial) resources.

Production frontiers may shift due to variation in endowments, farming technologies and economic institutions (Coelli et al, 2005). These traditional efficiency measures operating under a common production frontier are not comparable with those operating under different production frontiers (Chen et al, 2006). To the best of my knowledge all farmers' production efficiency researches conducted in the region (e.g.; Gebreeziabher et al, 2005; Gebreeziabher Z. et al, 2004; Gebregziabher K. et al, 2008; Shumet, 2011; Endris, 2010 etc) applied stochastic frontier model working under common production frontier (technology). Thus, to pinpoint the effect of technical inefficiency on productivity from the effect of environmental variation it becomes necessary to consider if production technologies differ across locations. If they are found different, comparing production efficiency of farmers within and among different locations would be possible using metafrontier analysis. The use of metafrontier analysis is justified because a frontier, which represents the best available technology for a given group, cannot be strictly compared across other locations/groups, unless they operate under the same production set. More precisely, using data on a group of DMUs it is possible to estimate production frontier, then it is common and straightforward to measure the relative performance

of all DMUs as compared to the ideal output represented by the frontier or best DMUs within the group. However, there is often considerable interest in comparing the performance of farmers across different groups. Unfortunately, such comparisons are only meaningful in the limiting special case where frontiers for different groups of farmers are identical. As a general rule, efficiency levels measured relative to one frontier cannot be compared with efficiency levels measured relative to another frontier. In addition, metafrontier analysis helps to estimate TGR which measures the deviation of group frontiers from the metafrontier. This study applied metafrontier analysis where comparison across groups with different production set is made possible. Therefore, this study will contribute new insights towards the endeavor in comparing production efficiency and TGR across different agro-ecological zones/groups with different production technologies (potentials).

Moreover, when cross sectional data are available we place a restriction on the distributions of composite error term (Aigner et al, 1977 and Fried et al, 2009). That is both inefficiency error term and random error term are assumed to be identically and independently distributed (IID), which is essential assumption in the maximum likelihood estimation (MLE) procedure. But in reality production efficiency, whether it is time varying or not, can be correlated over time. Precisely, farmers could need some time to make reasonably efficient use of the new/ modern inputs through learning by doing (Ali and Byerlee, 1991 as cited in Gebreegziabher et al, 2005). Thus, current production efficiency can be determined by previous year's efficiency; "learning by doing" and/or the hypothesis of "efficient farmers remain efficient in all cropping seasons" might work. These problems can be relaxed in the presence of panel data which shows the advantage of panel over cross sectional data. Most of the previous studies conducted on efficiency in Tigray region use one time period data ruled by the above restriction. Thus, this study of production efficiency using panel data could contribute to reduce the dearth of panel data literatures in the region and country as well.

The most important point in this methodological approach is that farm-level technical efficiency measures could be affected with differences in production possibilities. Farmers in some environments might be incapable of achieving high levels of productivity due to their unfavorable production environment. Therefore, productivity of farmers largely depends on their

resource endowments and physical constraints mainly climate and rainfall they faced (Mariano, 2011). Climatic constraints, unlike the application of traditional inputs, go outside farmers' direct control and hence farmers in different environments could face varying humidity, temperature and rainfall. With this set up, farmers are expected to have differing capabilities to achieve productivity growth. Thus, comparing the performance of farmers in such environments with varying potential of productivity using technical efficiency score obtained from stochastic frontier analysis (SFA) become misleading for policy interventions.

On the other hand, farmers can fit their production systems and management strategies, to the environment they are working in over long period of trial and error process extended over generations of farmers. They could adapt their cropping system to the variations in hydro and thermal growing seasons by choosing location-specific technologies that suit their environmental conditions. The differences in technology sets applied and resource endowments across environments lead to a diverse sets of feasible input–output combination available to farmers. This brought a need for estimating separate production frontiers to different groups of farmers so as to understand their respective levels and components of productivity accurately.

And finally, separate estimates of TE and TGR could be used to devise proper policies and programs for performance improvement through changes to the management and working structure of farmers or changing the production environment; for example, building infrastructure such as roads and ports, deregulating financial markets etc.

1.3 Study objectives

This study will examine empirically whether there exist efficiency difference and technology gaps among farmers and localities respectively; and explore the factors that determine the efficiency level and productivity across farmers under different Environmental groups.

1.3.1 Specific objectives

The specific objectives are;

i. Estimating technical efficiency and technology gap ratio of smallholder farmers in different environmental locations;

ii. To compare technical efficiency and technology gap ratio differences of farm households across different agro-climatic zones (Environmental groups).

iii. To investigate institutional factors, household and farm (plot) level characteristics affecting farmers' production inefficiency.

iv. To recommend possible policy measures for improving farmers' agricultural productivity and income.

1.4 Research questions

i. Are farmers technically efficient in organizing their production, as hypothesized by Schultz?

ii. Is there any production efficiency and technological gap variation of farmers within and among different locations?

iii. What are the factors that explain the variation in production efficiency?

1.5 Significance of the study

It is evident that agriculture productivity is a perquisite for economy progress in less developed countries like Ethiopia. Therefore, to achieve such policy goals dealing with productivity and efficiency of farmers is vital. Estimating the extent and pinpoint the sources of inefficiency indicates the possibility of increasing productivity by appropriately solving the inefficiency components without increasing the resources base. Moreover, when the effect of technological gap ratio is disentangled from inefficiency it is possible to design programs directed at improving production environment by building infrastructures or programs to change the managerial and working structures of the production environments.

This study separates the components of productivity in to technological gap ratio and technical inefficiency components by applying stochastic Metafrontier analysis. These results are expected to give some policy highlights designed to increase agricultural productivity by identifying the extent and determinants of inefficiency. Besides it contribution to the rarely available panel data

and metafrontier literatures in our country, it could serve as stepping stone for undertaking further research in the country.

1.6 Scope and limitations of the study

The study is conducted in Tigray Regional State using the data collected by HARITA project in collaboration with Mekelle University, Department of Economics. Three weredas; Raya Azebo (RA) from southern zone, Qolla Temben (QT) from central zone and Saesie Tsaeda Emba (STE) from Eastern zone are selected and household level data for the year 2009 and 2010 were collected. These areas are drought prone locations in the region so that the findings of this paper based on this data will not be representative result for the whole country or Tigray region and hence this may not be conclusive result for other parts of region and the country. So these facts should be taken in to account in using the result of this study for further research.

So long as the study is confined in a few weredas and some of the data was collected in drought years, its external validity could be weak and generalizations from the findings of the study to other parts of the country/region should not be made without further researches. Moreover, the emphasis of this research was on crop production and household level inefficiencies within crop production might not necessarily indicate overall household inefficiency; because households could possibly devote more of their attention to livestock and other nonfarm activities. Besides, given the severe drought that is observed in these years in some areas of the research site, farmers could be forced to engage in other alternative sources of income to ensure their survival. So that the result of this study should be seen from this light, and these facts make it clear for conclusive evidence at a wider scale (regional, national and different periods) more study is needed.

CHAPTER TWO

REVIEW OF RELATED LITERAYURE

2.1 Theoretical Literature

2.1.1 Productivity and efficiency concepts

Productivity = outputs/inputs." (Atkinson et al, 1995, 514)

"The two main sources of economic growth in output are increases in the factors of production (the labor and capital devoted to production) and efficiency or productivity gains that enable an economy to produce more for the same amount of inputs." (Baldwin et al, 2000)

Productivity and Efficiency are the most commonly used concepts in the field of social science. Seemingly, similar and interchangeably used terms but they are of two different concepts (Oyeranti, 2000 and Coelli et al., 1998). In the field of economics, technical efficiency is measured comparing the observed output against the feasible output in the frontier, where as productivity is defined in terms of the rate of output produced per unit of input utilized for production process (Färe and Grosskopf, 2004; Coelli, 1998; Samuelson and Nordhaus, 1995 and Antle and Capalbo, 1988). To construct the feasible ideal output upon which the actual output is compared, it is based on the concept of production function from which the idea of frontier production function is derived. Efficiency is a relative measurement, where it can only be measured with respect to some point of reference only; the point of reference is either an ideal level of performance or best practice frontier (Coelli et al. 2005).

Productivity, referring to total factor productivity is measure involving all factors of production (Coelli et al, 1998). Measures of productivity such as labor productivity in a factory, fuel productivity in power stations and land productivity (yield) in farming are often called partial measures of productivity. They can provide a misleading indication of overall productivity (performance) when considered in isolation. Based on the type of data they need and assumption they require different techniques can be applied for productivity analysis. Some are least-squares econometric production models, total factor productivity (TFP) indices, data envelopment analysis (DEA) and stochastic frontiers. The first two techniques assume all DMUs are technically efficient and applied for time series data used to technical change analysis. In

contrary to this, the latter two models use for measuring the relative efficiency of DMUs and technical change when panel data is available.

Growth in productivity can be achieved through different ways (Balk, 2001) though most of the time decomposed into technological change and technical efficiency (O'Donnell and Coelli, 2005 and Atkinson and Dorfman, 2005). Technical efficiency is interpreted as a relative measure of managerial ability of DMUs to produce the maximum output given technology constant, whereas technological change involves the "jumps" in the production function resulted from the application of better practices and development efforts (Ahmad and Bravo-Ureta, 1995). Many studies conducted on productivity involve the use of production frontiers describing the technical relationship between inputs and outputs. They measure and estimate the maximum output attainable from a given bundle of inputs and technology (Coelli, Rao and Battese, 1998). Production frontier reflects the current state of technology used by a firm. Therefore, productivity improvements through technological change are represented by an upward shift of the production frontier while improvements through technical efficiency are reflected by firms operating closer to the frontier. The presence of inefficiency in production indicates that output could be increased without requiring additional inputs given the prevailing technology (Coelli 1995 and Coelli, Rao and Battese, 1998).

Studies by Anderson and Feder (2007) and Ahmad and Bravo-Ureta (1995) found that the driving forces behind the efficiency and technological change differ. Research and development activities are the driving forces for technological change, while education and experience are factors for improving technical efficiency. Thus, it makes important to decompose productivity growth into technological change and technical efficiency components when designing policies directed at improving performance (Antle and Capalbo, 1988). Technological and managerial gaps are defined by differences in production between farmers' actual practices and the best practices that exist at any point in time. Thus, narrowing of both the technological and management gaps is needed in order to improve productivity.

The two most frequently applied approaches for estimating technical efficiency are the non-parametric linear programming (data envelopment analysis) and stochastic frontier analysis. DEA suffers from the criticism that it does not take in to account the possible influence of

measurement error and other noise in the data (Coelli, 1995). Moreover, it imposes linear production function with fixed proportion. The second approach uses econometrics tool to estimate a stochastic frontier function and the inefficiency component of the error term. The weakness of this approach is that it imposes an explicit and possibly restrictive functional form on the technology. However, SFA is chosen here as it permits the estimation of the determinants of inefficiency of the producing unit and control the effect of noises.

2.1.2 Historical Variant Stochastic Frontier

Traced back to formalized work of Farrell (1957) where technical inefficiency is defined as the deviation of actual out from the idealized frontier isoquant (Green, 2007), studies were conducted in many fields within agriculture, manufacturing and service sectors etc. The technique of frontier analysis has been described by Farrel in 1957 while the mathematical framework to handle frontier analysis was established only after 20 years by Charnes et al. (1978). These authors coined the term Data Envelopment Analysis and this seminal paper provided fundamental mathematical aspects for frontier analysis. In productivity and efficiency analysis of DMUs, the interest lies in estimating a production frontier or cost function and the basic references in economic theory are Koopmans (1951), Debreu (1951) and Shephard (1970). Following the fundamental theoretical work of Debreu (1951), Farrell (1957), Shephard (1970) and Afriat (1972), new researchers have established a technique to measure efficiency. Aigner et al. (1977), Battese and Cora (1977) and Meeusen and van den Broeck (1977) provided the econometric methods. On the other hand, linear programming methodology whose implementation was made transparent by Charnes et al (1978) was introduced for applications at about the same time.

Following the influence of Farrell (1957) exerted on Aigner and Chu (1968), Seitz (1971), Timmer (1971), Afriat (1972) and Richmond (1974) the manner directed to the development of SFA (Kumbhakar and Lovell, 2003). Despite the difference in the contributions these authors in a number of important respects, all of them estimated a deterministic production frontier, either using linear programming techniques or by modifications to least squares techniques requiring all residuals to be non-positive. Finally, SFA originated with the work of two separate papers from Meeusen and van den Broeck (MB) (1977) and Aigner, Lovell, and Schmidt (ALS) (1977).

The ALS and MB papers shortly followed by a third SFA paper from Battese and Corra (1977). All the three original SFA models shared the composed error structure and can be expressed in the following form:

(1)$Y_i = X_i\beta + (V_i - U_i)$ ……(i)

,i=1,...,N,

Where, Y_i is the production (or the logarithm of the production) by the i-th firm; x_i is a vector of (transformations of the) input quantities applied by the i-th firm; β is vector of unknown parameters to be estimated; the V_{it} are random variables which are assumed to be IID $N(0,\sigma_V^2)$, and independent of the U_i which are non-negative random variables which are assumed to account for technical inefficiency in production and are often assumed to be IID $N(U,\sigma_U^2)$.

The original specification has been used in a vast number of empirical applications over the last decades; has also been altered and extended in a number of ways. These extensions were on the specification of more general distributional assumptions for the U_i, such as the truncated normal or two-parameter gamma distributions and others; the consideration of panel data for time-varying technical efficiencies; the extension of the methodology to the application of cost functions and also to the estimation of systems of equations and so on (Coelli, 1996). Some of researchers providing wide-ranging reviews on this matter are Forsund, Lovell and Schmidt (1980), Schmidt (1986), Bauer (1990) and Greene (1993) etc.

According to FOrsund, Lovell, and Schmidt (1980; 14), the main weakness of the stochastic frontier model is that decomposing individual residuals into their two components was not possible. So that it is impossible to estimate individual technical inefficiency of observations. The solution was obtained from works of Jondrow et al. (1982) (JLMS) in which either the mean or the mode of the conditional distribution was proposed to provide estimates of the technical inefficiency of each producer in the sample. Following the possibility of obtaining producer-specific estimates of efficiency the appeal of SFA has greatly enhanced (Kumbhakar and Lovell, 2003). Later on, modification on the distributional assumptions of the error term and area of application are expanded sooner. Since half normal and exponential distributions assigned to the

one-sided inefficiency error component and were single-parameter distributions researchers soon developed more flexible two-parameter distributions. Afriat and Richmond, Greene (1980a,b) proposed a Gamma distribution and Stevenson (1980) proposed Gamma and truncated normal distributions. Lee (1983) proposed more flexible distribution, the four-parameter Pearson family of distributions. Despite all this the two original single-parameter distributions remain accepted distributions in the majority of empirical works. The JLMS technique used only to provide an estimate of overall cost inefficiency. However, decomposing the estimated overall costs inefficiency in to separate technical and allocative inefficiency remains a problem. For the first time, Schmidt and Lovell (1979) accomplished the decomposition of the composite error term for the Cobb–Douglas cost function case, while Kopp and Diewert (1982) obtained the decomposition for the more general translog case.

Until an improvement was made by Cornwell, Schmidt, and Sickles (1990), Kumbhakar (1990) and Battese and Coelli (1992), early panel data models worked assuming efficiency is time-invariant. The longer the time, the less reasonable this assumption becomes as efficiency could vary through time. Therefore, if efficiency is expected to vary across producers or through time, investigating for the responsible factors determining efficiency variation is important. It is then followed by two competing approaches; two stage approach and the single stage approach. In a two-stage procedure efficiencies are estimated in the first stage and then the estimated efficiencies are regressed against a vector of explanatory variables in a second stage. This approach now a day is recognized as one which is inconsistent in its assumptions regarding the independence of the inefficiency effects in the two estimation stages. Two-stage estimation procedure is unlikely to give estimates which are as efficient as those that could be obtained using a single-stage estimation procedure (Huang and Liu, 1994; Coelli and Battese, 1995). Later on studies including those of Kumbhakar, Ghosh, and McGuckin (1991), Reifschneider and Stevenson (1991), Huang and Liu (1994) and Battese and Coelli (1995) have adopted a single-stage approach where the explanatory variables are included directly into the inefficiency error component simultaneously. In this procedure the mean and the variance of the inefficiency error component are hypothesized to be a function of the explanatory variables incorporated there in.

Despite these growth and extensions to SFA, its working assumption was found to be restrictive and unrealistic in some cases. One of the most important working assumption in TE measurement is that individual DMUs (farms) included in the frontier being estimated operate under the same level of technology. The violation of this assumption biases TE estimates as output differentials emanating from technology and environment differentials could be considered as TE differentials. DMUs with higher technology and /or favorable environment could appear more efficient than they are. Stochastic Metafrontier model, the most recent variant of stochastic frontier models, thus, comes in to existent to handle such problems. Formally, following the estimation of Battese and Rao (2002) and Battese, Rao and O'Donnell (2004), stochastic metafrontier production function that envelops all the deterministic components group stochastic frontiers in the industry is expressed as:

$$y_{it}^{*} = f(x_{it}, \beta^{*}) = e^{x_{it}\beta*} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(12)}$$

$$i = 1,2,3 \ldots N; \quad t = 1,2 \ ; \ N = \sum_{j=1}^{J} Nj$$

Where, β^{*} denotes the vector of parameters of the metafrontier function such that$X_{it}\beta^{*} \geq X_{it}\beta_{j}$, for all i observations, i.e. parameters can be obtained by minimizing the sum of absolute deviations (MAD), solving the following linear programming:

$$\min L = \sum_{i=1}^{N} |f(X_{it}, \beta^{*}) - \ln f\left(x_{it(j)}, \beta_{j}\right)| \ldots\ldots\ldots\ldots\ldots\ldots \text{(13a)}$$

$$\text{S.t} \quad f(X_{it}, \beta^{*}) \geq f\left(X_{it(j)}, \beta_{j}\right) \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(13b)}$$

for all i observations

This analytical approach used in this study adopted the concept of a meta-production function as an envelope of neoclassical production functions. It, in spite of operating under different group specific production technologies, assumes all producers in an industry (agriculture) have potential access to the same technology. Following this concept, Battese, Rao and O'Donnell (2004) and O'Donnell, Rao and Battese (2008) have developed stochastic meta-frontier (SMF) model to estimate productivity differences between groups of DMUs. SMF function is used to compute comparable technical efficiency scores when group frontiers vary and technological gap

ratio (TGR) among groups and individual producers with a group. The technical efficiency resulted relative to MF is the product of TGR and TE relative to group specific frontiers.

The most important point in this methodological frame work is that farm-level technical efficiency measures could be affected with differences in production possibilities. Farmers in some environments might be incapable of achieving high levels of productivity due to the physical constrain imposed by their production environment which eventually contributes to spatial inequalities in income. According to Mariano (2011), the productivity of farmers largely depends on their resource endowments and they are faced with physical constraints mainly climatic variation that influences their decision-making and production operations.

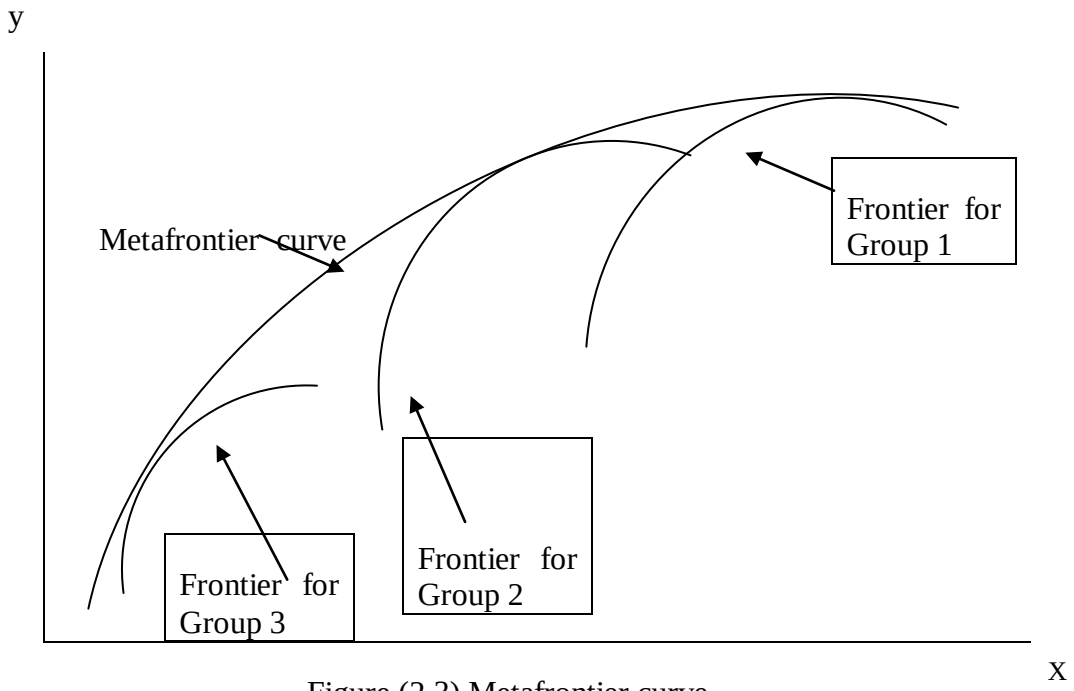

Figure (2.3) Metafrontier curve

Climatic constraints, unlike the application of conventional inputs, go outside their direct control and hence farmers in different environments face varying intensity of sunlight, temperature and rainfall. With this environmental set up, farmers are expected to have differing capabilities to achieve productivity growth. Thus, comparing the performance of farmers in environments with varying capability or potential of productivity using technical efficiency score obtained from SFA become misleading for policy interventions. On the other hand, farmers can make in order, their production systems and management strategies, to the environment they are working in.

They can fit their cropping system to the variations in hydrological and thermal growing seasons, choosing location-specific technologies that suit their environmental conditions. The differences in technology sets applied and resource endowments across environments lead to a diverse sets of feasible input–output combinations that show spatial and inter-temporal variations in productivity. These problems made, estimate separate production frontiers for different groups of farmers, essential in order to measure their level and components of productivity accurately. Comparison across groups with differing production technology and computations of TGR are undertaken using Metafrontier analysis.

2.2 Empirical Literature

The innovative work of Farrell (1957) on efficiency measurement ultimately influenced not only the development of DEA approach in 1966s and 1970s but also helped Aigner and Chu (1968), Seitz (1971), Timmer (1971), Afriat (1972) and Richmond(1974) to directly add on the development of SFA (Constantin et al, 2009). DEA do not accommodate the effect of noise, and therefore it was initially considered as a non- statistical technique where the inefficiency scores and the envelopment surface are 'calculated' rather than estimated (Murillo-Zamorano, 2004). But most of the literatures related to the measurement of efficiency have employed either on any of the above parametric or non-parametric methods.

Using a 10 years longitudinal data for 25 irrigated and 25 non irrigated farmers (Kalirajan and Shand, 2001) found slow rate of increase in technical efficiency in the two samples over time. They suggested that the restraint on technical efficiency was lack of information about the best practice techniques of the technology. This finding was contradicting to what was hypothesized by Ruttan (1977). With the problem of information asymmetry the shift in observed frontiers of farmers towards the true potential frontier is slow, consistent with learning by doing process. Farmers could grow close to full knowledge of their perceived production functions and of market conditions so that they can achieve higher levels of allocative efficiency at a relatively rapid rate. Mean while, improvements in technical efficiency are needed in the long run, to sustain improvements in economic performance.

According to Barker et al (1985), all farmers were not applying homogeneously best practice techniques whilst adopting the new rice technology caused by environmental, technical and/or socio-economic constraints. They found that there were efficiency differentials among farmers. About 67% of the yield gap, between the actual and the potential yields, was attributed to technical inefficiency of not following the best practice path technology. In addition to this, more than dozens of cross sectional studies have confirmed wide inter firm variations in technical and allocative efficiencies even many years after technology adoption (Huang and Bagi, 1984; Kalirajan, 1990 and Squires and Tabor, 1991).

Education has multifaceted effect on agriculture; raised productivity through increases in physical capital and purchased inputs or mobilizing active labor force to other competing sectors. Appleton and Balihuta (1996) found a positive association between education and agricultural productivity among Ugandan farmers. Four years of formal education were found raised production by seven percent. Education also increased productivity of neighboring farmers through its spillover effects. In contrast to this, education lead to a greater openness to new ideas and modern practices thereby affecting agriculture negatively as the more qualified individuals could leave farming to look for better employment in other sectors of the economy. Weir and Knight (2004) found that there are substantial and significant benefits to education in increasing average production, and shifted out the frontier by improving the level of technical efficiency. Parikh et al. (1995) in a two-stage estimation procedure of stochastic cost frontiers for Pakistani agriculture, found education, the number of working animals, credit per acre, and the number of extension visits significantly increased cost efficiency. On the other hand, larger farms and a more subsistence orientation considerably decreased cost efficiency.

Coelli and Battese (1996), Wang, Wailes, and Cramer (1996) and Seyoum et al. (1998) found that older farmers are less technically efficient than younger farmers and that family size and per capita net income are both positively related with production efficiency. Off-farm employment was negatively associated to efficiency, perhaps because households with off-farm employment have limited time allotted to manage their farms.

According to Anderson and Feder (2007), Extension services help to reduce, among farmers, technology gaps by speeding up the transfer of technology and efficiency gaps through helping

them become better managers. They are bridging communication channels in between scientists and farmers to facilitate both adoption and adaptation of technology to local conditions. It should be clear that extension has greatest impact at the early stages of technology dissemination, where awareness gap exists on new technology. As farmers become increasingly aware of a specific technology, the impact of such extension would diminish until the opportunity and need for more information-intensive technology arises (Ibid). Seyoum (1998) added that farmers who have access to extension services found more technically efficient than those who have not. Solis, Bravo-Ureta and Quiroga (2008) used data from 639 farms in El Salvador and Honduras found a positive relation between productivity and output diversification, TE and off- farm income and human capital and agricultural extension.

Metafrontier approach recently developed by Battese and Rao (2002), Battese, Rao and O'Donnell (2004) and O'Donnell et al. (2008) used to estimate and compare the efficiency of production units that have access to different production possibilities sets. This framework has been applied widely in the literature to evaluate the efficiency of groups of firms in industries as such as (education e.g., McMillan and Chan, 2004, Worthington and Lee, 2005; finance e.g., Kontolaimou and Tsekouras, 2010 and agriculture e.g., Chen and Song (2008), O'Donnell et al., 2008 as cited in O'Donnell, 2011). After its development, metafrontier framework is widely applied for analyzing the performance of different production units. Boshrabadi Et Al., 2006 varietal differences of pistachio production in iran; Naceur, 2011 for performance analysis of selected Mena banks; Wang And Rungsuriyawiboon, 2010 for agricultural efficiency, technical change and productivity in China; Rao et al., 2010; Khrueathai Et Al., 2011 for measuring operation efficiency of Thai hotels; Mariano et al., 2011 for technical efficiency of rice farms dn different agro-climatic zones in Philippines etc are a few to mention.

2.2.2 Empirical studies for African agriculture

Ezeh (2004) as sited in Baten et al. (2009) suggested using SFM of the parametric approach is appropriate of when the interest is measuring efficiency in agriculture sector. This is because of the inherent stochasticity observed in agriculture data which hold back one form adopting non stochastic approach. Following this, for this particular study the parametric method of SFA of efficiency estimation is appropriate approach.

Numerous of studies were conducted on productivity and efficiency estimation of African agriculture using parametric or non parametric techniques. Some of these studies have revealed a productivity growth of African agriculture in the 1960s, falling off in the 1970s and a recovery of productivity in the early 1980s (Rezek et al, 2011). FAO (2009) has reported an annual productivity growth rate of 0.6% for the years 2000–2007 while and 2.9% from 1997 to 2007. Nkamleu (2004) using MF approach studied agricultural sector of 16 African countries from 1970 to 2001. He found results supporting the view that technology gap plays an important part in explaining the ability of agricultural sectors in one region to compete with agricultural sectors in different regions in Africa. He has explained that the 0.1% per annum productivity growth estimated was the result of an average increase in TE equal to 0.6% per year combined with a 0.5% annual decrease in technological progress. The technological change component was observed to fluctuate widely suggesting that its promotion had not been consistent during the period. In these eleven out of the sixteen countries, efficiency increased more than technology.

In a study conducted on a total of 47 countries, it was argued that population pressure on land was the major explaining factor for faster growth in agriculture productivity. This result is consistent with findings of Boserup (1965) and Hayami and Ruttan's (1985) through 'induced innovation' hypothesis. On the other hand, De Janvry and Sadoulet (2001) using a general equilibrium model found that Africa is benefitted significantly from the direct effects of technology adoption.

Thiam and Bravo-Ureta (2003) in their study of technical efficiency measures of peanut producers in Senegal, found an average technical efficiency of 70.3%. Another study by Binam et al. (2004) using a sample of 450 farmers practicing slash and burn agriculture was conducted in Cameron. It was reported an average technical efficiency of 77% and 75% for groundnut mono crop and maize-groundnut farming systems respectively. Access to credit, soil fertility, and social capital, distance of the plot from the road and access to extension services were found to explain the differences in TE. More precisely at least four years of schooling, better access to credit, living in fertile regions and club or association membership make farmers more as efficient compared to without. On the other hand, the distance of the plot from the main access

road and access to extension services had a negative relationship with technical efficiency farmers.

According to Kibaara (2005) and Msuya et al (2008) in their analysis of technical efficiency of smallholder maize farmers Both in Kenya and Tanzania, found male headed households to be more efficient than the female counterparts. Meanwhile, Njuki et al. (2006) studying productivity differences between male and female managed farms in the Eastern and Central highlands of Kenya found that farms managed jointly by males and females had the highest TE at 77%, followed by those managed by males with a mean TE of 62% while farms managed by females had the lowest TE at 56%.

Finally, in Africa including Ethiopia researches employing metafrontier technique for TE and TGR of agriculture is too scarce. But there is still evidence of productivity gaps in African agriculture. Therefore, knowing the driving forces behind technical efficiency and technological change can guide policy decisions in improving productivity. This study will contribute in reducing the dearth of literature on the issue and thereby help better understand the sources of productivity gap by decomposing in to TE gap and TGR.

2.2.3 Empirical Researches in Ethiopia

In our country Ethiopia, it is evident that there is a dearth of empirical works on technical efficiency of farming systems across agro-ecological zones. In addition to that, except the works of Medhin and Köhlin (2008), there is no other study conducted applying metafrontier for decomposing the TE and TGR effects on productivity. Their study employs stochastic metafrontier approach to investigate the role of soil conservation in small-scale highland agriculture for the four groups of plots. They constructed plot-level stochastic frontiers and metafrontier technology-gap ratios were estimated for three soil-conservation technology groups and a group of plots without soil conservation. They reject SF in favor of SMF implying there is significant technological difference among farmers in these groups and found farmers experiencing soil and water conservation technology are more efficient.

There are large numbers of studies which are conducted to investigate the TE of farm households in Ethiopia including Tigray region, area of interest for this study. Most of the previous studies

conducted mainly concentrated on the efficiency and the determinants of inefficiency for farmers in a given environment. Some of them are Abrar, 1998; Hailu et al.,1998; Belete et al. ,1993; Admassie and Heidhues, 1996; Seyoum et al. , 1998 ; Gebreegziabher et al, 2005; Mariam and Garth, 1993; Weir and Knight, 2000; Bamlaku et.al, 2001; Nigussie, 2001; Ahmed et.al, 2002; Arega, 2002; Mulat and Bekele, 2003; Arega et.al, 2005; Temesgen and Ayalneh, 2005; Makombe et.al, 2007; Wubeneh and Ehui, 2006; Bamlaku et.a,l, 2009; Ulimwengu, 2009; Mulat and Bekele, 2003. Some additional literature is found on land issue focusing on the efficiency of the land tenure arrangement of the country. It includes Ahmed et al, 1998; Tesfay et al, 2005; Tesfay, 2006 and Kassie and Holden, 2007). Tesfay et al. (2005) in their study of the technical efficiency of peasant farmers in Tigray region, compare technical efficiency levels between own and shared-in plots. They found farmers have higher level of technical efficiency scores on own plots than on sharecropped-in plots. Besides, they pointed out that tenants, placed in villages with good annual average rainfall and good quality plots, have higher level of efficiency whereas densely populated villages revealed lower level of inefficiency, as farmers are expected to manage their small plots more intensively. On the other hand, Kassie and Holden (2007) using eviction and kinship as efficiency triggering factors, they found higher productivity in sharecropped in land as compare to own cultivated land. But all of these studies do not consider the variation of production possibilities across the comparison groups. Applying DEA, deterministic frontier where the short fall of observed in production from the frontier was assumed to be due to technical inefficiency, Belete et al. (1993) estimated the technical efficiency of small-scale farmers in the central highlands of Ethiopia. But in a situation where crop production is rain-fed, as is the case in Ethiopia, the impact of stochastic noises is clearly unavoidable. It has to be noted that agricultural production is nature reliant and affected by a host of factors that are beyond the control of farmers. In this regard, the impact of several demographic, socio-economic and institutional factors on the efficiency of farmers could not be overlooked.

Admassie and Heidhues (1996), for the farmers in central high land of Ethiopia using stochastic frontier production function, tried to separately determine and compare the level of technical efficiency of the two groups, one representing modern technology users and the other consisting of relatively traditional farmers that do not use modern technology. However, they did not

consider the variation in production possibility frontier among the comparison groups, as long as theoretically argue there is technology difference between groups. Moreover, they did not mention factors that affect technical inefficiency variation. Abrar (1998) in his study of identifying the Sources of Technical Inefficiency of Ethiopian Farmers apply a Single Stage Stochastic Frontier Inefficiency Model. He pointed out that farm size, age, household size, and off-farm income are the major determinants of TE in highland Ethiopia. Hailu et al. (1998) studied the technical efficiency of farmers in the eastern highlands of Ethiopia, Oromia region. They applied stochastic frontier production function for this study and analyzed the level of inter-farm technical efficiency. However, factors that determine technical inefficiency were not investigated and this makes it incomplete.

Gebreegziabher et al (2005) studied the production system of peasant farmers in Hintalo and Enderta districts of Tigray region, northern Ethiopia, using stochastic frontier production function. They apply single step approach of efficiency estimation and hence, simultaneously determine farmer-specific technical efficiency levels and determinants of inefficiency at household level. They found that productivity differences among farmers are relatively small and this could be because of farmers are living in the same environment, adjacent districts. Moreover, the study also revealed land size and oxen ownership are significant contributors of productivity increments, whereas engagement in off-farm activity was found to decrease inefficiency levels.

Gebregziabher et.al (2008) applied stochastic production frontier using a single-step efficiency estimation approach to analyze performance of irrigated and rain-fed smallholder agriculture. They found farmers are more inefficient on their irrigated plots than on rain-fed plots. Endris (2010), to test the existence of agricultural farm household inefficiencies and deal with their determinants in the Geba catchment area used Cobb-Douglas stochastic frontier production function. Farmers were found with 67 % technically efficient suggesting significant potential in crop production through reducing technical inefficiencies. Age of the households head, family size, number of crop types cultivated, and access to irrigation were found to influence the level of farm household inefficiencies.

Despite dozens of technical efficiency studies conducted, it is still an important area of great concern due to the fact that measurement of technical efficiency has relevance for policy intervention. In our country Ethiopia, modern resources are meager and opportunities for adopting better modern technologies are scarce. The economy largely depends on rain-fed and very traditional agriculture practices. Therefore, such efficiency studies are vital, as policy intervention may need to have prior information and helps decide whether to continue with the existing technology by improving the efficiency of less efficient farmers or to introduce a new technology. Therefore, this research will contribute by providing up to date information considering the agro ecological variation and methodological extension from the above studies.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Study Area Description

Tigray Regional state is located in northern part of Ethiopia neighbored by Eritrea in the north, Sudan in the west, Amhara regional state in south and Afar regional state in the east. The state is located at 12°15-4°57 longitude and 36°27- 39°59 latitude. Tigray is one of the smallest regions among the nine administrative regional states of Ethiopia both in terms area surface (80,000 sq. miles) and number of population (4,314,456) according to CSA, 2007. Regarding the sex composition of the population, 49.2 % of the populations are males and the remaining 50.2% are females. On the other hand, in terms of settlement, 19.5 % of the region population is living in urban areas where as 80.5% is living in the rural areas of the region. The population growth has decreased from 2.67 % before the 2006 census to 2.5 % in the 2007 census (CSA, 2008). Tigray, based on altitude, can be divided into five traditional agro ecological zones, namely, Bereha (less than 500 m.a.s.l.), Kolla, Woina Dega, Dega and Wurch (over 3200 m.a.s.l.) (Gebreegziabher, 2005).

Source; Adopted from Mohammed, 2011

According to CSA of 2007, Census Tigray regional state has an estimated total population of 4,314,456 of whom, 2,124,853 are men and 2,189,603 are women. From this total population, urban inhabitants are 842,723 or 19.53% of the total population. With its estimated area of 50,078.64 square kilometers, the region has an estimated density of 86.15 people per square kilometer. In Tigray regional state there are six administrative zones including Mekelle town, the state capital and comprising a total of 47 weredas (districts) and 673 Tabias (sub-districts).

The region is relatively dry and is subject to frequent drought and farming relies primarily on rainfall which is strongly seasonal and erratic. It ranges from 450 mm to 980 mm annually (Samuel, 2012). The main cropping season (meher) is from mid-June to September, when rains are concentrated. There are three altitude zones: Qolla (lowlands), Weyna-Dega (midlands) and Dega (highlands). Lowland crops include maize, pearl millet and sorghum; midland crops are wheat, barley and teff whereas in highland areas barley and potatoes are the dominant crops. Pulses and lentils, oil seeds, vegetables and spices are also produced across the highlands (see USAID, 2009; Howard & Smith, 2006 cited in Samuel, 2012). Out of the total grain produced, cereal crop took the lion's share (89.5 %), followed by oilseeds (7%) and pulses (3.5%) are in their order (CSA, 2011).

3.2 Data source and sampling technique

Data source of the study is a household level panel data set extracted from rural agriculture based Farm Household Survey conducted by the HARITA (Horn of Africa Risk Transfer for Adoption) project with the collaboration of Mekelle University. The project undertakes two surveys, a [1]baseline survey and a follow-up survey, each of which collected information about the same households. The total number of farm households, respondents, in the survey was 774. This survey is a two-round survey covering two cropping periods – 2009 and 2010 harvesting seasons. These sets of primary data contain information on total agricultural production, inputs applied for production and socioeconomic variables. Then the production function, the relationships between inputs and outputs, is precisely estimated using of household level panel data.

[1] *Woreda is Ethiopian name for the district whereas, Tabia is regarded as the lowest administrative hierarchy (Negash. Z, 2009).*

With regard to sampling technique of the survey, it made use of a combination of purposive, proportional and systematic random sampling methods. First, three Weredas (Saesie Tsaeda Emba, Qolla Tembien and Raya Azebo) were selected purposively; of which eight Tabias (sub Weredas; two from Saesie Tsaeda Emba, three from Qolla Tembien and Raya Azebo for each) were selected on proportional basis i.e. Weredas with larger number of Tabias are given more weight. Then after, Tabias' sample size was determined proportionately, it was followed by systematic random sampling application to come up with a total of 395 respondents. In March and April of 2011, follow-up survey was conducted and collected information about the 2010 growing season for the same households that were interviewed in the baseline survey. Respondents were asked about the same decisions and outcomes for the 2010 growing season in the follow-up survey as were asked for the 2009 growing season in the baseline survey.

The survey gathered detailed information from farmers about crops cultivated, conventional inputs used in production, loans taken, and yields in the 2009 and 2010 growing season through retrospective questions. The survey also collected data about the amount of each type of assets they own, amount and type of labor devoted to crop production (in days) during the growing season to 5 major production tasks: preparation/ ploughing, sowing, weeding, harvesting and threshing. The types of labor were family's own labor, hired labor, labor of family's own oxen, and labor of hired oxen. Information about socioeconomic characteristics of households; their participation in various community organizations, income, plot characteristics, and household characteristics and institutional characteristics on which the analysis is exclusively dependent is also collected. All data on production decisions, yields, participation in organizations and household characteristics consists of information provided by the farmer him/herself.

3.3 Theoretical frameworks and Model specification

3.3.1Theoretical Frameworks

Even if the beginning of the efficiency estimation is traced back to the 1950s (Farrell, 1957), there have been a mounting interest on its use in benchmarking performance, predominantly as a means of identifying best practice and improving the efficiency of resource use within the agricultural industry (Defra, 2004 and SAC, 2009 as cited in Barnes et al, 2011). Following the

works of (Aigner et al, 1977; Meeusen, 1977; Pitt and Lee, 1981; Jandrow et al, 1982; Battese and Coelli, 1992, 1995 and Kumbhakar, 2002) etc, the application of parametric frontiers in the estimation of TE in agriculture is demonstrated in a number of empirical studies. In recent years, the stochastic frontier approach has proved to be the most popular method because of its ability to take into account measurement error in the output and stochastic elements of production. Accordingly, it helped disentangle the effect of noise from the effect of inefficiency.

The skill of production units to transform resources into outputs depends not only on the technical efficiency of the DMUs but also by exogenous variables that capture the environment in which production activity takes place. When accounting for these variables, it is useful to distinguish between non-stochastic variables that are observable at the time key production decisions are made (eg., degree of government regulation, type of firm ownership, age of the labor force) and unforeseen stochastic variables that can be regarded as sources of production risk; for instance; weather, pest infestations, events of any type that might lead managers to seek some form of liability insurance (Daraio and Simar, 2007 and Fried et al., 1999). Thus, if the environmental variables are not adequately taken into account, some DMUs could seem efficient when they are inefficient or vice- versa, which is misleading. Operational environment, here, is defined as all explanatory factors that interfere, to a larger or lesser extent, with the DMU performance.

As proposed in Battese and Coelli (1992) a stochastic frontier production function for panel data, do have firm specific effects that are assumed to be distributed as truncated normal random variables, are also permitted to vary systematically with time. This model is specified as follows:

$$Y_{it} = f(x_{it}\beta + V_{it} - U_{it}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$i=1\ldots N, \qquad t=1\ldots T$

Where, Y_{it} is (the logarithm of) the production of the ith firm in the tth time period; x_{it}, is a $N\times M$ matrix of (transformations of the) input quantities of the ith firm in tth time period; βs, are $M \times 1$ vector of parameters to be estimated; V_{it} are random variables which are assumed to be IID $N(0,\sigma_V^2)$, and independent of the;

$U_{it} = (U_i \exp(-\eta(t-T))$…… (2)

Where, the U_{it} are non-negative random variables which are assumed to account for technical inefficiency in production and are assumed to be IID as truncations at zero of the N (μ, σ_U^2) distribution,η is a parameter to be estimated showing whether efficiency is time varying or not. The variable t is specific time the data is collected and T the total number of surveys conducted.

According to Coelli (1996) a number of empirical studies (e.g. Pitt and Lee, 1981) have employed stochastic frontiers and predicted firm-level efficiencies using these estimated functions. They regressed the predicted efficiencies upon firm-specific variables such as managerial experience, ownership characteristics, etc to identify some of the reasons for differences in predicted efficiencies between DMUs in the industry. This analysis has been accepted as a useful exercise, despite a two-stage estimation approach. However, the procedure is inconsistent in its assumptions regarding the independence of the inefficiency effects in the two estimation stages and is questionable to provide efficient estimates that are comparable to those that could be obtained using a single-stage estimation procedure.

This problem was overcome after Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991) proposed stochastic frontier models in which the inefficiency effects (U_i) are expressed as an explicit function of a vector of firm-specific variables and a random error. Battese and Coelli (1995) extended the approach by proposing an equivalent model stated above and allowing the application of panel data. The model they specified is expressed as;

$Y_{it} = x_{it}\beta + V_{it} - U_{it}(Z_{it}, \delta)$ …….... (3)

Where, Y_{it}, x_{it}, and β are as defined earlier: and V_{it} are random variables which are assumed to be IID, N (0,σ_V^2), and independent of μ_{it}; which are non-negative random variables which are supposed to account for technical inefficiency in production and are assumed to be independently distributed as truncations at zero of the N(μ_{it}, σ_U^2); where:

$\mu_{it} = \delta_i Z_{it}$ ……..…… (4)

Where, m_{it} is the efficiency of the i-th DMU in period t; w_{it} is a p×1 vector of variables which may influence the efficiency of the i-th farm at t-th time period; and δ, is 1×p vector of inefficiency parameters to be estimated. The model specified above encompasses other model specifications as its special cases; if we set T=1, w_{it} contains the value one and no other variables except the constant term, then the model will be condensed to the truncated normal specification in Stevenson (1980), where δ_0 will have the same interpretation as the μ parameter in Stevenson (1980). However, the model defined by equation (3) and (4) does not have the model defined by (2) as a special case and neither does the reverse apply. Thus, these two model specifications are non-nested and hence no set of restrictions can be defined to test one specification over the other.

Following the panel data works of Battese and Coelli (1992, 1995) that got considerable acceptance in recent years, stochastic frontier will be preferred to data envelopment analysis although the later relaxes the restriction imposed on the functional forms and the former control measurement error, random error term and specification error. Suppose that, in the jth group, there are sample data on N_j farmers that produce a given output using various inputs and the stochastic frontier model for this group will be defined by;

$$y_{it(j)} = f(X_{it(j)}, \beta_{(i)})e^{V_{it(j)} - U_{it(j)}} \quad \ldots\ldots (5)$$

i= 1, 2... N_j; t = 1; 2 ... T; j = 1, 2 ... R

$y_{it(j)}$, denotes the output, of the ith farmer in j^{th} group at the tth time period, and $x_{it(j)}$ is NxM vector of logarithms of inputs that are used by the ith firm (farmer) at the tth time period in j^{th} group, β is a vector of unknown parameters to be estimated, U_{it} which are defined by the truncation (at zero) of the $N(U_{it}^{j}, \sigma_{ut}^{2})$ distribution are a non-negative variable associated with technical inefficiency and V_{it} is a symmetric random error assumed to be identically and independently distributed as, $N(0, \sigma_{vt}^{2})$) that accounts for statistical noise.

Efforts are made for the extensions of the original stochastic frontier model in the estimation of technical inefficiencies to accommodate differences in technologies across locations and DMUs

in the industry. Stochastic metafrontier framework proposed by Battese and Rao (2002) and Battese, Rao and O'Donnell (2004) that allows not only an examination and comparison of the technical inefficiencies of firms but also provides a measure of the technology gap ratio will be employed in this study.

3.3.2 Model specification

On the road of addressing the specified objectives, this paper employed both stochastic group frontier and stochastic Metafrontier analysis for estimating the outcome variables. The group frontier, in this case, represents the state of technology pertaining to the transformation of all inputs into agricultural output restricted to a particular climatic zone (environment). Stochastic metafrontier, in contrast, represents the state of technology at the regional level which is unrestricted and sometimes referred as the boundary of metatechnology set.

3.3.2.1 Stochastic Group frontiers Estimation

It is plausible to hypothesize the presence of sub-technologies that represent the production possibilities of groups of firms (farmers). This study consider the case where the universe of DMUs can be divided into J (>1) groups, and we suppose that resource, regulatory or other environmental constraints may preclude DMUs in certain groups from choosing the full range of technologically feasible input–output combinations in the meta technology set. Rather, the input–output combinations available to firms in the jth group are contained in the group-specific technology set. Following the panel data works of Battese and Coelli (1992, 1995) that has got considerable acceptance in recent years, stochastic frontier is preferred to data envelopment analysis. Although the DEA relaxes the restriction imposed on the functional forms, it assumes linear production function and all DMUs are facing the same environmental, institutional and technological reality. SFA on the other hand control measurement error, the effect of random error term etc. Suppose that, in the jth group, there are sample data on N_j farmers that produce a given output using various inputs.

If a log-linear functional form (e.g., Cobb-Douglas or Translog) is assumed; the stochastic frontier model for this group will be specified as in Battese, Rao and O'Donnell (2004);

$$y_{it(j)} = f(x_{it(j)}, \beta_j)e^{V_{it(j)} - U_{it(j)}} \quad \text{.....6a}$$

$$y_{it(j)} = e^{X_{itj}\beta_j + V_{it(j)} - U_{it(j)}} \quad \text{.....6b}$$

Where, $y_{it(j)}$ denotes the output, the GVOs of the ith farmer produced using a technology in j^{th} location at t^{th} time period, and X_{it} is NxM vector of logarithms of inputs that are used by the ith firm (farmer) at the tth time period in j^{th} location, β is a vector of unknown parameters to be estimated, U_{it} is a non-negative variable associated with technical inefficiency and V_{it} is a symmetric random error that accounts for statistical noise. In this study, there are three groups categorized according to their geographic locations (Weredas). Stochastic frontiers of each wereda (location), as in equations (2) will be predicted using computer program FRONTIER4.1 software that employs a single stage estimation procedure written by Coelli (1996). In addition to the parameters β and σ, the predicted TE of each farm unit in the group and the log-likelihood functions will also be reported in the frontier output.

$$\sigma^2 = \sigma^2{}_{vit} + \sigma^2{}_{uit} \quad \text{..... (7)}$$

And

$$\gamma = \frac{\sigma^2{}_{ut}}{\sigma^2} \quad \text{..... (8)}$$

The parametric approach specifies a functional form to represent the relationship between output and inputs. A preferred functional form fulfils the properties identified by Coelli et al. (2005), such as flexibility, linearity in parameters, regularity and parsimony. The second order flexible transcendental logarithmic (translog) function developed by Christensen et al. (1973) satisfies these properties and is widely used in econometric estimation. However, the increased flexibility comes at a cost of more parameters to be estimated and this may could rise econometric difficulties (eg., multi-collinearity).The more Parsimonious Cobb–Douglas functional form, which is a simplistic (particular) form case of Translog production function, is employed to represent the production model. A hypothesis test is made to test the adequacy of representation

of the data.

Moreover, stochastic frontier for the pooled data is going to be estimated in the same manner. The pooled estimation is critical to the formation of the metafrontier, as one should perform the log likelihood ratio (LR) test. After estimating the frontiers for each group and pooled as in equation 2, a likelihood ratio (LR) test will be executed to verify if the technologies in three different agro-climatic zones (locations) can be represented by a common technology (from pooling the data).

A more general and flexible Translog production function will be written as;

$$\ln y_{it(j)} = \sum_{1}^{N} \beta_j \ln X_{itj} + \frac{1}{2}\sum_{1}^{N}.\sum_{1}^{M} \beta_{nm} \ln X_{nit} \ln Xmit + (Vit - Uit) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.9$$

The translog production function is defined in Equation (9), where, Ui represents the technical efficiency of the ith firm, and $\beta_{nm}=\beta_{mn}$to satisfy the concavity property of the translog production function. Equation (9) can be estimated parametrically using the maximum likelihood estimation procedure with the assumption that the error terms have a truncated normal distribution. Generalized likelihood ratio test will be used to verify these hypotheses using the following test statistics calculation:

$$LR = -2\left\{ Ln\left[\frac{LH_0}{LH_1} \right] \right\} = \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9a)$$

$$LR == -2\{Ln(LH_0) - Ln(LH_1)\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9b)$$

Tests are undertaken in the due course of the research:

a. to select the best specification of production function (Cobb-Douglas or Translog) for adequately representing the dataset
b. for verifying the relevancy of stochastic frontier model in capturing the presence of inefficiency in production among farmers in the study area;
c. to check inefficiency determinant variables for the predicted TE and
d. To reveal whether stochastic metafrontier is adequate than stochastic frontier analysis for this study.

The null hypotheses to be tested on the due course of addressing the above points are stated as follows;

In all cases of hypothesis testing during this analysis, $L(H_0)$ in equation (9) is the value of the likelihood function of in favour of Cobb-Douglas SFM and $L(H_1)$ is the value of the likelihood function for the full translog stochastic frontier model. The null hypothesis and the alternative hypothesis are stated as follows.

i. H_0: the coefficient restrictions imposed on the squared and interaction terms of input variables are equal to zero;

   H_1: the coefficients of squared and interaction terms of input variables are different from zero.

ii. The inefficiency effects are absent from the composite error term of the stochastic frontier model, that is, all farmer in the three locations (Weredas); Saesie Tsaeda Emba, Qolla Tembien and Raya Azebo groups in the study area are efficient, is tested if H_0: $\gamma=0$ Vs. H_1: $\gamma>0$. The value γ will be computed by and reported in the Frontier output.

iii. Inefficiency variables in the inefficiency effects model defined by equation (4) don't explain the variation in the TE of farm households in the study area and will be tested as H_0: $\delta_1 = \delta_2 ... = \delta_n = 0$ and H_1: $\delta_0 + \delta_1 + \delta_2 + ... + \delta_n \neq 0$

iv. Farmers in the three different locations share the same production technology, that is stochastic frontiers for the three groups are the same and the parameters in their stochastic frontiers can be pooled.

To validate these stated hypotheses at the first and second, LH_0 and LH_1 are values of the likelihood function under null and alternative hypothesis respectively. First, production frontiers will be estimated using Cobb Douglas and Translog functional forms. The log likelihood ratio of the two functional forms is compared using generalized LR test whether the parameters on the squared and interaction terms of the variables included in the translog production function are together equal to zero. Immediately after specifying adequate production function using the values of LH_0 and LH_1, the first task to test is the existence of the inefficiency component of the composed error term in the stochastic frontier model. This is made in order to decide whether the

traditional average production function (OLS), which don't ultimately involves non-negative random error term specification best fits the data as compared to the stochastic frontier model (SFM) specified for this study. If the null hypothesis (γ=0) is accepted against alternative hypothesis (γ>0), then the SFM is identical to OLS specification indicating that there is no inefficiency problem within these crop producing farmers. The second hypothesis to be tested is simple and its objective as clearly described above in hypothesis (ii) is identifying variables contributing for farmers' inefficiency. It is to validate if the parameters of the inefficiency variables included in the model are together equal to zero.

Finally, for the last hypothesis testing, the values of the likelihood functions of the sum of the separate group frontier estimations and the pooled data will be compared. In a simple expression, LH_0 is the value of the log-likelihood function for the SFM estimated by pooling the data for three groups, and LH_1 is the sum of the values of the log likelihood functions of the separate groups (Greene, 2003). Its objective is to test for the feasibility of the traditional approach (SFM) before approving the use of stochastic metafrontier model (SMFM). If the null hypothesis of a common technology is rejected, the estimation will keep following the metafrontier framework (Battese, Rao and O'Donnell, 2004 and O'Donnell et al. 2008). Stochastic metafrontier is a useful concept when the aim of the analysis is to compare the efficiency of different groups (e.g., locations, regions, countries) when there is the suspicion that each group operates under different production environments and therefore their production frontiers are different. In this brief overview we follow O'Donnell et al (2008) procedure for estimating the metafrontier curve.

Based on suitable distributional assumptions on the inefficiency error term , U_{it}, half normal distribution will be chosen for avoiding complexity, input and output data for farms in the jth group can then be used to obtain maximum-likelihood (ML) estimates of the unknown parameters of the frontier defined by equation 1 & 2. Output- oriented TE estimates with respect to the group j frontier for the ith farmer can be computed from equation 2;

$$TE_{ijt} = \frac{y_{it}}{y_{ijt}^{max}} = \frac{e^{X_{itj}\beta_j + V_{it(j)} - U_{it(j)}}}{e^{X_{itj}\beta_j + V_{it(j)}}} = e^{-U_{it(j)}} \quad \text{.....} (10)$$

Equation (10) allows us to examine the performance of ith firm relative to the individual group frontier. In order to examine the performance of ith firm relative to the metatechnology set, the stochastic metafrontier production function approach is used. The stochastic metafrontier is a function that envelops the deterministic components of stochastic frontiers for different groups (O'Donnell et al, 2008). Initially, SMF was considered as envelope of stochastic group frontiers defined by all observations in different groups in a way that is consistent with the specifications of a stochastic frontier model by Battese and Rao (2002). This specification was found fall below the estimated group stochastic frontiers in some areas inconsistent to the theoretical framework of metatechnology set. Later on, it is modified by Battese, Rao and O'Donnell (2004) to envelope the deterministic part of stochastic group frontiers.

So as to model the relationship between TE and those variables which might put forth an impact on the level of TE, we follow Wang and Schmidt (2002) and Alvarez et al. (2006). The model specified for the random variables u fulfills the scaling property, i.e. the fundamental shape of the distribution remains constant for all observations. Specifically, we apply a heteroscedastic frontier model, which assumes heteroscedasticity of the one-sided error term. This error term reflects factors under the farmer's control, and since large farms have more factors under their control, the one-sided error term is likely subject to size-related heteroscedasticity (Caudill and Ford 1993). Therefore, following Battese and Coelli (1995), estimated technical inefficiency can be modeled as follows:

$$\sigma_{uit} = e^{\delta_i Z_{it}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Where, Z_{it} is a p×1 vector of farm-specific variables and household level factors (demographic, socio-economic and institutional factors) including a constant and δs are 1×p unknown vector of parameters to be estimated. Using the maximum-likelihood method, the parameters γ, the stochastic frontier model and inefficiency effects model can be consistently estimated with the variance parameters. In this case, X_{it} in equation 1&2 and Z_{it} are allowed to overlap (Alvarez et al. 2006; Wang and Schmidt 2002). Besides allowing for functions of inputs in the inefficiency model, the scaling property of the heteroscedastic model enables direct interpretation of inefficiency coefficients as semi-elasticity (Wang and Schmidt 2002). After estimating the group

frontiers including the frontier and inefficiency variables, a likelihood ratio (LR) test is executed to verify if the technologies in three different geographic locations can be represented by a common technology. If the null hypothesis of a common technology is rejected, the estimation will keep following the stochastic metafrontier framework (Battese, Rao and O'Donnell 2004).

3.3.2.2 Stochastic Metafrontier Model

Now a day Estimates of technical inefficiency in agricultural production are routine, however, they are suspensions provided that variations of production technology exist within sampled farmers. Such variations include changes in ways of doing things, differences in input attributes, differences in the type of production technologies, differences in environmental conditions as well as the type of crops they planted (Villano et al., 2010). Analyzing performance of farmers applying stochastic frontier model which is widely used technique with these technology differences risk attributing TE. The recent methodological variant in estimating technical inefficiency that minimizes such type of risks by specifying a metafrontier model for production (Battese and Rao, 2002; Battese et al., 2004 and O'Donnell, 2008) allows technology gap effects to be disentangled from technical inefficiency.

The stochastic frontier production function has been widely used in the study of technical efficiency. The difference between the stochastic frontier production function and the traditional production function is that the error term in the stochastic frontier production function includes a symmetric random error term and a non-negative technical inefficiency term. As not all producers are always successful in utilizing the given inputs to maximize output under a given technology, namely, not all producers are always technically efficient; the stochastic frontier analysis is more realistic. However, stochastic frontier analysis assumes that all producers operate under a given production technology, and thus, cannot be used to compare the performance of producers operating under different technologies. In order to address this issue, Battese, Rao and O'Donnell (2004) have developed a stochastic metafrontier approach to investigate technical efficiencies and technology gaps across different groups.

Metafrontier framework is a useful concept when the aim of the analysis is to compare the efficiency of different groups (locations, regions, countries) and there is a suspicion that each

group operate under different technologies and therefore their production frontiers are different. This analytical approach adopted in this study is an extension of the concept of a meta-production function as an envelope of neoclassical production functions developed by (Hayami and Ruttan (1971). The concept assumes all DMUs in the industry have potential access to the same technology despite operating under different production technologies. SMF methodology involves estimating different frontiers for different groups of DMUs, then measuring the distances between these group frontiers and the metafrontier. The metafrontier is a type of global frontier that envelops all the deterministic part of group frontiers. In spite of assessing the efficiency of individual production units with respect to the metafrontier, efficiency of DMUs is assessed relative to its own group frontier and then the production environment faced by the group is assessed by measuring the distance between the group frontier and the estimated stochastic metafrontier. The distances between different group frontiers and the metafrontier are referred as technology gap ratios (TGRs) or metatechnology ratios (MTRs). This TGR measures the potential improvements in group performance that could possibly resulted when production units are given access to the production technologies of all other groups in the industry.

The feasibility of the traditional approach (SFM) will be tested before approving the use of stochastic metafrontier model (SMFM). If the null hypothesis of a common technology is rejected, the prediction of technical efficiency will keep following the metafrontier framework (Battese, Rao and O'Donnell 2004). MF model is valuable when the analysis aims to compare the efficiency of DMUs in different groups operating under different technology sets, where there is the suspicion difference in their productive frontiers. In this brief the study will follow O'Donnell et al (2008) where the metafrontier that envelops the deterministic component of group frontiers is estimated using SHAZAM software. O'Donnell et al, (2004) also provide an econometric estimation of the metafrontier parameters using stochastic frontier analysis but will not guarantee to envelope group frontiers. To estimate the metafrontier, there is a need to find the function that best envelops the deterministic components of the estimated stochastic group frontiers, frontiers for Environmental variations (location) in our analysis. Formally, the metafrontier production function is:

$$y_{it}^{*} = f(x_{it}, \beta^{*}) = e^{x_{it}\beta*} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (12)$$

$$i = 1,2,3 \ldots N; \quad t = 1,2 \;\; ; \; N = \sum_{j=1}^{J} Nj$$

Where, β^* denotes the vector of parameters of the metafrontier function such that $X_{it}\beta^* \geq X_{it}\beta^*_j$, for all i observations, i.e. parameters can be obtained by minimizing the sum of absolute deviations (MAD), solving the following linear programming:

$$\min L = \sum_{i=1}^{N} |f(X_{it}, \beta^*) - \ln f\left(X_{it(j)}, \beta *_j\right)| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(13a)}$$

$$\text{S.t} \qquad f(X_{it}, \beta^*) \geq f\left(X_{it(j)}, \beta *_j\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(13b)}$$

, for all i observations

In this optimization problem, $\beta *_j$ are treated as fixed so that the second term in the summation is constant with respect to the minimization. Hence, (13a) can be equivalently solved by minimizing the objective function;

$$\text{Min} \quad l^* \equiv \mathbf{x}\beta^* \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(14a)}$$

s.t

$$f(X_{it}, \beta^*) \geq f\left(X_{it(j)}, \beta^*_j\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(14b)}$$

Where, $\boldsymbol{X}$ refers the row vector of means of elements of the x-vector for all observations in the dataset. In terms of the estimated MF, the observed output of the ith farm, defined by the SPF for the jth group in equation 2 can alternatively be expressed as follows:

$$y_{it} = e^{-u_{ijt}} \times \frac{e^{x_{it}\,\beta}}{e^{x_{ti}\,\beta^*}} \times e^{x_{it}\beta^* + v_{ijt}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(15)}$$

Where the first term on the right hand side is the TE with respect to group frontiers (TE_i) as in equation (3) and the second term is, what Battese and Rao (2002) term the technology gap ratio (TGR), which is expressed as the meta-technology ratio (MTR) for the observation for the sample farm involved:

$$TGR_{ijt}\,(MTR_{ijt}) = \frac{e^{X_{it\,(j)}\beta^*_j}}{e^{x_{it}\,\beta^*}} = \frac{y_{ijt}}{e^{x_{it}\,\hat{a}^*}} \Big/ \frac{y_{ij\,t}}{e^{X_{it\,(j)}\beta^*_j}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(16)}$$

MTR is a ratio of output for the frontier production function for the jth group relative to the potential output defined by the MF function, given the observed inputs (Battese, Rao and O'Donnell 2004), that is, the ratio between the efficiency estimate against the group frontier and the efficiency estimate against the MF (TE_i^*). In deriving the Meta technology ratio (MTR) or TGR and technical efficiencies relative to the metafrontier, the research will note that (O'Donnell et al., 2008). It lies between zero and one and captures productivity differences between different groups of technologies, TGR, (Battese and Rao, 2002; Battese, Rao and O'Donnell, 2004). Alternatively, (17) is arranged to decompose TE_i^* into the group TE estimate and MTR:

$$\mathrm{TE_{it}}^* = \mathrm{TE}^{9}_{\mathrm{tj}} \times \mathrm{MTR_{ijt}} = \frac{y_{it}}{e^{x_{it}\beta^*}} \quad \text{.....} \quad (17)$$

Choice of distributional specification is sometimes an affair of computational simplicity. Estimation of some frontier models is programmed in some software packages but not in others. For example, FRONTIER can be used to estimate half-normal and truncated-normal models, while LIMDEP can also be used to estimate the exponential and gamma models. Theoretical considerations may also influence the choice of the distributional specification. For instance, some researchers evade the half-normal and exponential distributions because they have a mode at zero, implying that most inefficiency effects are in the neighborhoods of zero and coupled with measures of technical efficiency would be in the neighborhood of one. The truncated normal and gamma models permit for a wider range of distributional shapes; sadly, this flexibility comes at the cost of computational complexity insofar as there are more parameters to estimate.

One closing remark when choosing between models is that a difference in distributional assumptions can lead to difference in predictions of technical efficiency (Coelli et al, 1998). Yet, when we rank DMUs on the basis of predicted technical efficiencies, rankings are often quite robust to the distributional choice and in such cases, the principle of parsimony favors the simpler half-normal and exponential models. We can also use estimates from the truncated-normal model to test the null hypothesis that the simpler half-normal model is adequate. The null and alternative hypotheses are; the mean technical efficiency and estimated coefficients are equal to zero or different from zero. If the model has been estimated using the method of maximum

likelihood, we can use either the z- or the LR-test; but different testing procedures can lead to different conclusions in finite samples.

3.3 Variable selection and description

The variables included in this production model are agricultural output, labor in man days, fertilizer in value, seed in its value, land in hectare, oxen power in oxen days, farm equipment in value and binary variables for irrigation and time. The inefficiency model is estimated by household characteristics, physical and socioeconomic factors of production such as education, age, farm size, number of workers, asset ownership, access to credit and extension services etc. The variation in output levels largely depends on the quantity of inputs used in production while differences in technical efficiencies are explained by productivity-enhancing factors.

Output (Y): This paper considers agricultural outputs. This distinction enable to explicitly know the differences in production techniques involved in producing these crops. It is also true that different agricultural commodities in these broadly defined groups can also exhibit differences in their production while the compression in this study is restricted at aggregate level. Here, the output aggregates used refers completely to the final output (value of agricultural output net of seed) in different environments and these aggregates are computed using regional average prices.

Land; This variable refers to the land under permanent crops or land area currently cultivated expressed in hectares. Land under permanent crops is the land that is cultivated with crops that hold on the land for long periods and need not be replanted after each harvest that includes land under chat, coffee, fruit trees, nut trees and vines but exclude if the land is under trees grown for wood or timber.

Seed; the farmers in this study area apply local seeds and sometimes improved seeds. Since these seeds vary in type it is better represented using the valued of total seed used for agriculture (planting) crops.

Farm equipments; This variable includes the value of total number of equipments used by the farmer for preparation of the land and thereby producing agricultural output.

Labor: The labor variable refers the total number of used in agriculture, which is defined as all persons engaged in the operation of the farm whether family labor, salaried employees or unpaid workers in man days. These man days' refinements are required to account information on differentials in skill levels and the numbers of hours worked on the farms.

Fertilizer: This input is quite difficult to measure because of different types of fertilizers applied by farmers. Thus, the total value of fertilizer used by these farm household is taken for this study.

Oxen days; it refers the amount of draft power used by the farmer represented by the number of oxen days applied for agricultural activity.

Irrigation; this is represented using a dummy variable 1 if the household has cultivated irrigable and 0 otherwise. This is hypothesized to have a positive sign on the productivity effect.

Manure; it measures the amount of manure used in kilogram (Kg) by each farmer in the study area. This manure applied is expected to have appositive effect on the productivity of farm households.

Non- Agricultural income: This variable is a binary variable with a value of 1 if household got off farm income (remittance or any other source out of their farming) in that production year, and 0, otherwise. This variable can have a twofold effect on the production the farmer as being involved in off farm activities may make farmers spend more time on off farm activities relative to farm activities and hence put negative effect on their agricultural outcome. On the other hand, the income generated from off farm activities may be used to purchase agricultural inputs and hence exert a positive complement for the farm activities. Moreover, off farm income can enhance the risk management capacity of farmers.

Access to credit: This variable would be examined as binary variable; 1 represents if the household had faced a credit constraint during that production season, and 0 otherwise. Credit constraint refers the case where the farmer applies for loan but failed to get that loan. As the loan availability reduces capital constraints of the farmers and facilitates the timely application of inputs, it is expected to have a positive influence on their technical efficiency. Due to this reason,

the sign of the coefficient of this variable in the inefficiency model is expected to be positive. It means it is hypothesized to have positive effect on inefficiency.

Farm size; it represents the size of cultivated land in binary form, where equals 1 if cultivated land is greater than the mean area of cultivated for the whole households and 0 otherwise. This is expected to give positive effect on technical inefficiency of farm households.

Agricultural extension workers' contact: this refers if the farmer got any extension service from any extension agents during the 2009 and 2010 cropping seasons. It is a binary variable representing 1 if the farmer visits extension agent and 0 otherwise. Framers' extension visit helps them get information on the technology adoption and how to improve productivity. Farmers' continuous contact with the extension workers is expected to increase efficiency and hence the variable expected having positive sign.

Gender of household head: it is a binary variable 1 if gender of the household head is male and 0 otherwise. Male headed household would have better opportunity to carry out frequent follow up and supervisions of the farm activity on their plot and this put positive effect on technical efficiency of farmers. Contrary to this, male headed households might be efficient as they can challenge the problem. Thus, gender of the household head could result positive or negative effect on efficiency.

Age of the household head: This variable is measured by the year age of the household head. The increase in age of the household tends farmers to adapt the environments and get more experienced and challenge the problem he/she faced in the past. The degree of inefficiency is made-up to decline as age of household increases and negative coefficient is expected in the inefficiency model. It is a continuous variable that takes a value greater than zero measured in years and this can have positive or negative efficiency effect.

Education: education is proxy by the average number of years spent in school by the household members. On average Educated farmers are expected to acquire, analyze and evaluate information on different inputs, outputs and market opportunities much better than illiterate farmers. Thus, household education is taking in to account on that most farm management decisions for which education is decisive are made by each household member. The coefficient

of this variable is, therefore, expected to be negative in the technical inefficiency effect. In this perspective average years of education for the household will also be used as alternative for the analysis. Education also can have positive relationship with technical inefficiency of the farm household.

Family size; is discrete variable defined as the total number of household members living under one roof. It is hypothesized to have positive effect on efficiency.

Farm Size; is continuous variable measured in hectare the farmer has to manage during the particular cropping season. This is hypothesized to have either negative efficiency effect.

Soil Type; is a dummy variable which represents the types of soil in the study area in hectare; vertisoil, cambisoil, luvisoil, leptosoil and others. From this we can infer the major type of soil in the study area.

Sharecropped in land; this is a continuous variable representing the ratio of sharecropped in land to the total area of cultivated rain fed land by each farmers in the study area.

Number of crops planted; this show the total number of crop types the farmer has cultivated during that production year. This variable can have either positive or negative effect on the performance of farmers.

Finally, Cobb-Douglas production function with technical inefficiency effect model for panel data set applied for this study is specified as:

$$\ln(Y_{it}) = \beta_0 + \beta_1 \ln X_{1t} + \beta_2 \ln X_{2t} + \beta_3 \ln X_{3t} + \beta_4 \ln X_{4t} + \beta_5 \ln X_{5t} + \beta_6 \ln X_{6t} + V_{it} - U_{it}(\delta_i z_{1t}) \quad (18)$$

Where:

$Y_i =$ is the dependent variable representing the value of outputs for i-th farm household at th time period.

$\ln =$ Represents natural logarithms

$\beta_i^{'}s$ = Represent unknown parameters (elasticity coefficients) to be estimated

X_1 = total amount of labor in man-days used in crop production (both family and hired labor) ith farm household

X_2 = the size of land measured in terms of hectare used for cultivation by ith household

X_3 = the total value of seed used in the production process (in Birr)

X_4= total amount of oxen-days used in crop production

X_5 = access to irrigation (dummy variable)

X_6= year dummy variable

V_{it} = a disturbance term with normal distribution properties as explained above

U_i = farm specific inefficiency error term

There are two methodological approaches for analyzing the sources of technical inefficiency on stochastic production frontier. One approach is the two-stage estimation procedure in which first the stochastic production function is estimated, from which inefficiency scores are derived while, in the second stage the derived efficiency scores are regressed on explanatory variables using ordinary least square methods or Tobit regression. This two step approach has been criticized on grounds that the farmer's knowledge of its level of technical inefficiency affects its input choices; hence inefficiency may be dependent on the explanatory variables. Thus, it leads to biased technical inefficiency estimation due to its inconsistent assumptions. The second approach is a one stage simultaneous estimation approach as in Battese and Coelli (1995), in which the inefficiency effects are expressed as an explicit function of a vector of farm-specific variables. The technical inefficiency effects are expressed as:

$$\text{?}_{it} = \delta_i Z_{it} + \varepsilon_i \text{ ---------- } (3.17)$$

Where for farm household i, z is a N×p vector of observable explanatory variables and δ is a p×1 vector of unknown parameters to be estimated. Thus, the parameters of the frontier production function are simultaneously estimated with those of an inefficiency model, in which the technical inefficiency effects are specified as a function of other variables. This one-stage estimation approach is implemented using FRONTIER 4.1 version written by Coelli et al. (1996). It provides coefficients for the technical inefficiency model in addition to the basic parameters for the frontier function. Despite Socioeconomic and demographic factors as well as plot-level

characteristics are likely to affect the inefficiency of smallholder farmers, only some explanatory variables are used for this analysis.

$$\text{?}_{it} = \delta_0 + \delta_1 z_{1t} + \delta_2 z_{2t} + \delta_3 z_{3t} + \delta_4 z_{4t}\ \ \delta_4 + \delta_5 z_{5t} + \delta_6 z_{6t} + \delta_7 z_{7t} + \ \delta_8 z_{8t} + \delta_9 z_{9t} + \delta_{10} z_{10t} + \varepsilon i ---------- 3.18$$

Z_1 = plot size in hectare they own

Z_2 = access to extension service access for wage income

Z_3 = Gender

Z_4 = Education

Z_5 = age of the household head

Z_6= Age square

Z_7 = Household size

Z_8= access to credit

Z_9= number of crops planted

Z_{10} = ratio of sharecropped in land

$\delta_i =$ Unknown inefficiency parameters to be estimated

εi = Error term.

Chapter Four

Empirical Results and Analysis

4.1 Descriptive Statistics Results

In most developing countries including Ethiopia, agriculture remains a prime source of livelihood for the vast majority of the people, an important earner of foreign exchange earnings for country, and as a result its performance remained a center of concern within the government. One of the great problems faced by these countries is that: efforts to predict the consequences of agricultural policies are often confounded by the complex behavioral patterns characterizing farm households in semi-commercialized rural economies. That is to say, most households in agricultural areas produce partly for sale and partly for their own consumption. For most rural farming societies in the areas where there is market imperfection, production and consumption decisions are inseparable (Bardhan and *Udry*, 1999). Demographic structure within the farm households, ownership and access to resources and the environmental situation created by institutions around are closely linked to the productive capacity of households and their economic and social well-beings (Ellis and Freeman, 2004). They also purchase some of their inputs (fertilizer, for example) and provide some (such as family labor) from their own resources.

Although it is not a sufficient condition, all markets should exist and should be perfect for separability to exist. Historically, economists thought that the labor market was the one least likely to exist for peasant farms. That view has been changing, however, since active rural labor markets have been found according to several studies (Rosenzweig, 1978; Spencer and Byerlee, 1977; Bardhan and udry, 1979; Rosenzweig and Wolpin, 2000 and Binswanger and Rosenzweig, 1984) although they are not necessarily perfectly competitive ones.

4.1.1 Household and Farm Characteristics of sampled Households

4.1.1.1 Household level Characteristics

Before the investigation of econometric results looking the simple descriptive statistics of the three target groups (environments) in terms of the basic explanatory variables: household, farm

and institutional characteristics seem to be imperative. To compare farm households in terms of their household level characteristics in these three locations, pair wise analysis is made and hence mean values are compared across groups.

Table 4.1 Descriptive Statistics of Sampled Farm household Characteristics in three locations

Variable		Raya Azebo N=(158)	Qolla Temben N=(189)	S. Tsaeda Emba N=(149)	Total N=496	Mean (=) F- test, (P> F)	Variance = χ 2, (P> χ 2)
HH Gender	Mean	0.79	0.65	0.74	0.72	4.39	4.2768
	St.dev	0.41	0.48	0.44	0.45	0.0129	0.118
HH Age	Mean	42.39	42.78	47.90	44.19	8.77	5.4703
	St. dev	11.53	13.78	13.12	13.10	0.0002	0.065
Family size	Mean	5.90	5.16	6.05	5.66	9.47	3.0058
	St.dev	1.94	2.00	2.22	2.08	0.0001	0.222
Total work age	Mean	4.21	3.87	4.15	4.06	2.60	9.6259
	St. dev	2.58	2.32	2.95	0.86	0.4240	0.008
HH years Education	Mean	1.61	1.95	1.70	1.77	2.62	2.0134
	St.dev	2.50	2.77	2.55	0.76	0.4686	0.365
Head Educat (Dummy)	Mean	0.36	0.41	0.39	0.38	1.13	0.3140
	St.dev	0.47	0.49	0.49	0.47	0.3233	0.855
Average HH education	Mean	1.58	1.89	2.28	1.91	9.05	0.0947
	St. dev	1.44	1.41	1.43	1.45	0.0001	0.954

F-test and χ 2-test are used to test mean equality using a pair wise analysis among groups and variations within a group respectively. The values beneath F and χ 2 tests are P- values.

Source: HARITA Survey data and own computation

The above table shows the demographic characteristics of farm households in three different environments, where the environmental grouping is based on wereda (Raya Azebo, Qolla Temben and Saesie Tsaeda Emba) in different locations. As it is indicated in table 4.1, 158, 186 and 149 of the sample respondents are drawn from Raya Azebo (RA), Qolla Temben (QT) and S.T. Emba (STE) weredas respectively. In terms of gender household headship 79, 65 and 74 percent of the respondents in these weredas respectively are headed by male. Hence, gender headship similarity of the households across these ecological zones is rejected at 5 percent significance level.

Comparing farm households in terms of their mean age showed that Raya Azebo and Qolla Temben wereda (with the mean age in years of, 42.3 and 42.8) are significantly different from wereda S.T. Emba (with mean age 47.9 years) at 1 percent level of significance. The statistically significant variation on the mean age of household heads in the study area is expected to account for the variation in agricultural practices in the study area. When comparison is undertaken based on mean family size across these locations, on average each household in Raya Azebo, Qolla Temben and S.T. Emba have 5.9, 5.2 and 6.1 members, respectively. Family size is one important demographic factor that may have multifaceted influence on agriculture practices of the farmers in general and productivity (efficiency) in particular. The equality of mean of household size among these groups is rejected at 5 percent level of significance as wereda S.T. Emba has larger family size compared to Qolla Temben. The family size of all respondents, on average, is 5.7 members per household and the mean age of all farm household heads in this study is 44.2 years. Finally, about 72 percent of the household are male headed households. To put in a nut shell, the RA wereda has highest male headship, lowest mean age of the household head as QT wereda has the lowest male head household headship. Conversely, the highest mean age of the head and largest family size is seen in STE wereda.

Education is another most important factor in determining the opportunities available to individuals in society and is closely linked to the productive capacity of households and thereby their economic as well as social well-being (Klasen, 1999). Similarly, 36, 41 and 39 percent of the respondents in Raya Azebo, Qolla Temben and S.T. Emba weredas respectively, have at least one year of formal education. Based on the simple descriptive statistical results the equality of percentage of educated households across groups is not rejected. When we look at the sample in its totality, 38 percent of the respondents have formal education. The other key facet of education which can have an effect on households' agricultural practice is the household average years of education. The dominancy of farmers in STE households persists on average years of household education while Qolla Temben and Raya Azebo are taking the next rank (place) respectively. The average years of education respectively for these groups are 2.28, 1.89 and 1.58 years while for the total sample it is 1.91 years of education. The equality of mean household years of education among location is strongly rejected at one percent level of significance. The other important aspect of household characteristics that could correlate with agricultural production

level of efficiency is the number of active working age household members. On active work age aspects the equality of mean across locations is not rejected at 5 percent level of significance.

4.1.1.2 Farm and plot level characteristics

The purpose of this study is to investigate the relationship of technical efficiency with household level and farm level characteristics. Table 4.2 reveals a pair wise analysis results for comparing farm household in three locations based on their socio-economic factors, farm characteristics and inputs they applied for their farm. As it is indicated in table 4.2 framers in Raya Azebo wereda on average have a largest farm size both in own farm size (1.25 hectare) and cultivated land size (2.08 hectare). Farm households in Qolla Temben having average own plot size and cultivated land size of 0.84 hectare and 1.01 hectare are the second large farm size holding area. Households in wereda S.T. Emba with average own plot size 0.59 hectare and cultivated land size of 0.6 hectare take the last places. Similarly, using these average land holdings, the equality of average farm size (both own and cultivated land) among the three ecologies is strongly rejected at one percent level of significance. This difference in farm size across locations is expected to have its own implication in productivity as well as efficiency of farm households.

The other important aspect of farm level characteristics that is hypothesized to affect farm performance is sharecropping. On this aspect, farmers in Raya Azebo wereda have the largest ratio of sharecropped in land. The smallest ratio of sharecropped in land is seen for the farmers in Qolla Temben wereda. The equality of ratio of sharecropped in land among these groups is rejected at 1 percent level of significance. The average own land, cultivated land and ratio of sharecropped in land size for all farmers is 0.9, 1.23 and 0.25 tsimad respectively. As it is indicated in table 4.2, about 35 percent of the total farmers have access to irrigation service. Access to irrigation in terms of location distribution Qolla Temben farmers have better (49 percent) followed by Raya Azebo (27 percent) and S. Tsaeda Emba (24percent). Using descriptive statistical tools, the equality of farmers in different locations with respect to access of irrigation is rejected at 1 percent level of significance. On average each farmer in the study area plant 2.74 types of crops. But the average number of crop types planted by each farmer has no difference across locations.

In addition, soil type is expected to have a strong influence on productivity and the type of technology to be adopted by farmers. Studies by different researchers such as Jaetzold et al., 1983; Pantzios, 2002 and etc revealed that soil type affects agricultural practices of farm households. Type of crops to be planted, the decision and the choice of technology type to be adopted and the returns from investment are among some aspects correlated with soil type (quality).

Table 4.2: Descriptive Statistics of farm level characteristics (in hectare)

Variable		Raya Azebo N=158	Qolla Temben N=186	S.T. Emba N=149	Total N=493	Mean (=) F- Test P> F	Variance(=)χ 2, p> χ 2
land characteristics of farm households							
Own Land	Mean	1.25	0.84	0.59	0.90	49.60	100.67
	St. Dev	0.78	0.56	0.33	0.64	0.0000	0.000
Cultivated	Mean	2.08	1.011	0.60	1.23	116.13	195.56
Land	St. Dev	1.23	0.83	0.34	1.07	0.0000	0.000
Sharecropped	Mean	0.35	0.17	0.23	0.25	7.66	42.414
In ratio	St. Dev	0.39	0.29	0.48	0.39	0.0005	2 0.000
Irrigation	Mean	0.27	0.49	0.24	0.35	15.44	4.5573
	St. Dev	0.44	0.50	0.43	0.48	0.0000	0.102
Crops Planted	Mean	2.84	2.62	2.77	2.74	2.27	0.0512
(#)	St. Dev	0.97	0.97	0.98	0.98	0.1043	0.975
Soil characteristics of the farm land							
Hutsa-Lepto	Mean	0.06	0.34	0.26	0.23	28.31	30.631
Soil	St. Dev	0.27	0.42	0.33	0.37	0.0000	8 0.000
Baekel- Cambi	Mean	0.18	0.17	0.06	0.14	7.25	149.96
Soil	St. Dev	0.43	0.31	0.15	0.32	0.0008	0.000
Walka- Verti	Mean	0.64	0.06	0.04	0.24	125.50	569.09
Soil	St. Dev	0.66	0.14	0.15	0.48	0.0000	0.000
Keyh-Luvisoil	Mean	0.16	0.07	0.12	0.11	4.35	85.073
	St. Dev	0.38	0.20	0.22	0.26	0.0134	5 0.000
Total output produced and Conventional inputs applied by farmers							
Output	Mean	2482.67	6399.59	7390.58	5445.64	2.74	177.59
	Sd	8121.20	25511.63	19840.82	19750.47	0.0659	0.000
Fertilizer	Mean	44.35	540.19	323.88	317.25	61.81	318.44
value	Sd	102.03	472.70	525.53	461.93	0.0000	0.000
Seed value	Mean	227.53	219.12	796.25	394.36	72.18	311.89
	Sd	310.67	209.32	794.71	551.66	0.0000	0.000
farm equipmt	Mean	969.34	297.81	1507.904	873.96	8.64	302.52
	Sd	2219.64	984.73	177.22	2716.16	0.0002	0.000

Labor	Mean	106.02	73.89	58.47	79.53	20.21	84.41
	Sd	91.72	56.69	44.92	69.76	0.000	0.000
Manure	Mean	141.79	290.52	440.71	287.95	8.55	73.370.
	Sd	378.06	707.43	738.14	641.75	0.000	000
Oxen Day	Mean	20.92	24.26	38.95	27.59	34.42	85.87
	Sd	12.85	18.55	27.52	21.58	0.0000	0.000
Institutional characteristics							
Credit	Mean	0.12	0.14	0.08	0.11	1.54	9.8950
Constraint	Sd	0.33	0.35	0.27	0.32	0.2150	0.007
Extension	Mean	0.87	0.82 0.39	0.80	0.83	1.75	6.1420
Service	Sd	0.33		0.40	0.38	0.1743	0.046
Remittances	Mean	.103	.071	.076	.084	0.51	4.342
	Sd	.305	.259	.266	.277	0.598	0.114

F-test and χ 2-test are used to test mean equality among groups and variations within a group

Source; Source: HARITA Survey data and own computation

As it is shown in the above table 4.2, there are at least four types of soils in the study area; Hutsa- Lepto soil, Baekel -Cambi soil, Walka- Verti soil, Keyh-Luvisoil and other types. In these study area as a whole the greatest share of soil type is held by Verti soil, Lepto soil Cambi soil and Luvi soil respectively. Walka- Verti soil is the dominant type of soil in Raya Azebo wereda; While Hutsa-Lepto soil is dominant soil type in Qolla Temben and S.T. Emba wereda. As comparison is made the equality of average land sizes in hectare with the same soil type is strongly rejected in all aspects of soil types at 5 percent level of significance. Therefore, we can infer in almost all dimensions (characteristics) of land; owned land size, cultivated land size, ratio of sharecropped in land, access to irrigation and soil types of the rained fed farm land owned by farmers vary with location.

As it is indicated in the same table, of the mean values of output produced and conventional inputs per hectare applied across three locations were compared. In this descriptive statistical analysis, all groups have statistically different mean value and the null hypothesis (equal mean) is rejected at 1 percent level of significance. The highest mean value of output per cultivated land is observed in STE while the smallest is in RA wereda. On the other hand, when we come across all conventional (Labor Day, oxen day, seed, fertilizer, farm equipment and manure) inputs applied per hectare of cultivated land on average; the equality of mean is statistically rejected at 1 percent significance level. Farm households in Raya Azebo wereda on average have the highest labor and lowest oxen day per hectare applied for production. Besides, they used smallest

amount of fertilizer and manure for their agriculture. Qolla Temben farmers in contrast to this, experience the highest fertilizer use. But their farm equipment and seed used in their farm have the lowest value relative to the other groups. Finally, farmers in S.T. Emba wereda, relative to the comparison groups, are observed with the highest values of seed and farm equipment. They are also highest in manure application but lowest in Labor Days used for agriculture.

Farmers in these three groups are also compared in terms of their institutional characteristics that encompass access to extension service and credit. The percentages of people that have accessed extension services are not statistically different across the three groups. In addition to this, percentage of farm households faced credit constraints are in these wereda is not dissimilar. The percentage of people who made contact with extension agents are about 83 percent of the sampled households where as, those with credit constraint are about 11 percent. In terms of these variables the equality access to institutions such as credit and extension services among groups is not statistically rejected even at 10 percent level of significance. Finally, the percentage of farmers those who receive remittance income from members currently outside their household are indicated in the same table. The figures across locations are 10.3%, 7.1% and 7.6% of the farm households for Raya Azebo, Qolla Temben and S.T. Emba respectively. Statistically the equality of percentages of households receiving remittance in these groups is not rejected at 10 percent level of significance.

4.2 Econometric Results and Discussions

4.2.1 Production frontier estimates and

4.2.1.1 Hypothesis Testing

Production frontiers with Cobb Douglass and Translog production functional forms using the pooled data and each geographical grouping (wereda) data set were constructed to test which one of functional forms adequately fit the data. The generalized Likelihood ratio (LR) test supported the rejection of the null hypothesis, implying the second order flexible translog production should be used for this analysis. But the Translog production suffers from too much multi-collinearity problem which affects the reliability and efficiency of estimated parameters. The mean variance inflation factor (VIF) of the translog production function is about 6128.94 (see in

the appendix) which is too severely high whereas, for the Cobb Douglas production function its mean VIF is 1.74. Since the estimated parameters from stochastic frontier are going to be used for constructing metafrontier curve and metafrontier parameters, the most parsimonious and first order flexible Cobb Douglas functional form with more efficient parameters is preferred to Translog functional form. In spite of everything, choice of functional form has insignificant effect on the overall results and limited effect on empirical efficiency measurement in particular (Idiong, 2007 and Joachim .et. al, 2004). Moreover, in one of the very few studies investigating the impact of functional form on efficiency Kopp and Smith (1980) concluded ‘‘*that functional specification has a discernible but rather small impact on estimated efficiency’’* and concluded functional form specifications have insignificant differences when the interest of the study is efficiency estimation. That is the rationale why Cobb-Douglas functional form has been extensively applied for the analyses of farm efficiency in developing and developed countries (Battese, 1992 and Bravo-Ureta and Pinheiro, 1993). Since the second order flexibility of TL functional form is obtained at a severe cost of multi-collinearity, the simpler and its special specification Cobb Douglas functional form is preferred for this study.

Therefore, production frontiers of Cobb Douglas functional form were constructed to undertake further likelihood ratio tests used for choosing appropriate model specifications. First of all, Stochastic frontier for the three geographic location basis groups and for the pooled sample are estimated using FRONTIER 4.1c (Coelli, 1996) computer program. From these estimated frontiers, LnH_0 and LnH_1 are computed for calculating generalized LR test statistic. LnH_0 is the log likelihood value of the stochastic frontier estimated using the pooled data while, LnH_1 is the sum of log likelihood values of the three estimate group frontiers. As it is shown in table 4.3, the log likelihood ratio (LR) test from the maximum likelihood estimator (MLE) shows LR test statistic 152 which is greater than its critical value at 12 degree of freedom and p-value of 0.000. This clearly indicated the need for the construction of SMF curve as the test strongly rejected the null hypothesis that stated homogeneity of technology among farmers in different environments.

SFA is appropriate to the data if stochastic frontiers across Environments do not differ; then it is possible to just use the pooled stochastic frontier. But stochastic frontier for the pooled data and three groups are constructed to know if the farmers in different groups share the same

technology. For this study stochastic metafrontier model was found to be an appropriate to compute[2] and compare the degree of inefficiency level among farmers in different geographic locations. Therefore, SMF which envelope the deterministic components of stochastic group frontiers was estimated using SHAZAM software by applying O'Donnell et al. (2008) estimation procedure. Because, it is found that these groups do not share the same technology as the null hypothesis is rejected using the value of likelihood ratio statistic. The null hypothesis was stated there is homogenous technology (production environment) across geographical groupings; between the three group frontiers and thereby all estimated parameters can be pooled together to construct a single production frontier up on which performance of DMUs are measured. The LR test results failed to accept the null hypothesis of no technological difference.

Table 4.3; LR test results used for testing the hypothesis in functional form and model specifications; SFM and inefficiency model

Null hypotheses	Test statistics λ	DF	Critical value $\chi^2_{v0.95}$	Decision
CD vs Translog pf	69.2	20	39.94	Translog is proper
SFA vs DEA				
Ho: $\delta^2=0$	5.04	1	1.96	SFA is proper
SFA vs OLS				
RAYA AZEBO				
H_0: gamma: $\gamma = 0$	6.09	1	2.706	SFA is appropriate
H_0: sigma: $\delta_1 = ... = \delta_{10} = 0$	67.3	10	16.274	TE effect model is proper
Qolla Temben				
H_0: gamma: $\gamma = 0$	20.7	1	2.706	SFA is appropriate
H_0: sigma: $\delta_1 = ... = \delta_{10} = 0$	54.7	10	16.274	TE effect model is proper
Saesie Tsaeda Emba				
H_0: gamma: $\gamma = 0$	17.7	1	2.706	SFA is appropriate
H_0: sigma: $\delta_1 = ... = \delta_{10} = 0$	39.9	10	16.274	TE effect model is proper
Total HHs				
H_0: gamma: $\gamma = 0$	101.4	1	2.706	SFA is proper
H_0: sigma: $\delta_1 = ... = \delta_{10} = 0$	180.6	10	16.274	TE effect model is proper
SMFA vs SFA				
Pool-ability of gfs				
H_0: $\beta_j=\delta_j=\gamma_j$	152	32	43.194	SMFA is proper

Source; 2012/13 own computation from HARITA data

[2] Grouping of farmers in to different environments is based on geographical location.

As it is clearly indicated in table 4.4, generalized likelihood-ratio test using a mixed chi-squared distribution confirms that the technical inefficiency term is a significant addition to the stochastic group frontiers and pooled models. The null hypothesis which states that, farmers are efficient and inefficiency term is not explained by inefficiency variables is also rejected at 1 percent significance level. The appropriateness of SFA over ordinary least square (OLS) is justified by the values of sigma and gammas. As can be seen in table 4.3, the value of gamma representing the variation of output due to the variation of inefficiency of DMUs in the pooled as well as group frontiers is statistically different from zero. Therefore, in the language of statistics, the null hypothesis stated as gamma is equal to zero will be strongly rejected at 1 percent level of significance. Hence, the presence of inefficiency is detected in the production of agricultural commodities. This reality made stochastic frontier model (SFM) suitable to analyze the data set at hand as compared to the OLS estimator that ignores the presence of inefficiency in production. Furthermore, from the values of gamma the null hypothesis stating inefficiency explanatory variables are not explaining the variation of inefficiency is rejected at 1 percent significance level. The likelihood ratio (LR) test statistics values of 67.3, 54.7, 39.9 and 180.6 for Raya Azebo, Qolla Temben, S.T. Emba and pooled frontiers respectively. As compared to the 16.274 which is their critical value, they are larger and enable for the rejection of the null hypothesis. They all confirm the technical inefficiency effect model is adequate to undertake the analysis as the null hypothesis, H_0:δ_1=...= δ_{10}=0 that says household level inefficiencies are not affected by household and socio-economic characteristics included in the model is also rejected at 1 percent significance level. Thus, the independent variables in our model do explain the variation of inefficiency among the farmers.

Moreover, a test is made whether stochastic frontier is better than the deterministic frontier-data envelopment analysis- that ignores the effect of unobserved factors beyond the control of DMUs. Based on the value of sigma squared found in the model, stochastic frontier analysis is preferred to the data envelopment analysis as sigma squared is significantly different from zero. This suggests the existence of factors not under control of farmers but able to explain the variation of output. The null hypothesis of H_0: δ^2=0 there is no stochastic effect on the variation of output is rejected at 5 percent level of significance for all frontiers. Therefore, SFA is preferred over OLS

[3]and DEA model specifications due to gamma values and sigma squared values respectively. Thus, likelihood ratio tests have clearly indicated the superiority of SFA over the two models. SFM takes account of factors unobserved but affecting the level of productivity as well as the inefficiency of farmers resulted from their household characteristics, farm characteristics and other socio economic characteristics.

4.2.2 Estimates of stochastic Production frontiers

Following the estimation of the stochastic frontiers for each of the three localities as well as the pooled data, a choice of functional forms using LR test estimates were made. Based on these estimates, for RA group and pooled data set translog production function was found appropraite while Cobb Douglas production function was favored over the less restricted TL production function for group QT and STE. LR estimates of the stochastic frontier translog and Cobb Douglass production parameters of study units are presented in Table 4.3. In metafrontier construction one of the restriction imposed is group frontiers should have the same function form specification. Moreover, while using TL production function, its inherent problem is the issue of multi-collinearity among the explanatory variables. This multi-collinearity affects the efficiency of the estimated parameters as it increases the magnitude of the standard errors. Besides, the TL production function does not satisfy the second order condition criteria in all cases for testing concavity. This is the reason that Cobb-Douglas functional form has been extensively used in the analyses farm efficiency in developing and developed countries (Battese, 1992 and Bravo-Ureta and Pinheiro, 1993).

Using the generalized LR test result, the pool-ability of estimates across groups is strongly rejected at 1 percent level of significance. This implies that there is a difference in the estimated coefficients of these different locality group frontiers due to a difference in the input output set off choices available to the farmers in different environments.

[3] Theoretical values for a mixture of chi-squared distributions are provided in Kodde and Palm (1986).

Table 4.4 estimated parameters of frontier and inefficiency variables

Stochastic frontier parameters		Total	RA	Q T	STE	Metafrontier parameters
Constant	β_0	6.054***	3.585***	7.001***	7.775***	8.911
		(0.538)	(0.965)	(0.674)	(1.059)	
Labor	β_1	0. 488***	1.034***	-0.388**	0. 582*	-1.342
		(0.179)	(0.386)	(0.196)	(0.341)	
Land	β_2	0.577***	-0.043	1.592***	1.189	3.118
		(0.280)	(0.478)	(0.400)	(0. 827)	
Seed	β_3	-0.149	-0.542*	0.261**	-0.110	0.617
		(0.121)	(0.294)	(0.131)	(0.216)	
Oxen-day	β_4	-0.108	0.314*	0.109	-0.274	0.290
		(0.092)	(0.180)	(0.110)	(0.174)	
Irrigation	β_5	0.384**	0.566*	0.328*	-0.137	
		(0.161)	(0.309)	(0.196)	(0.313)	2.322
Year	β_6	0.560***	1.140***	0.627	0.476*	
		(0.167)	(0.273)	(0.189)	(0.276)	0.000
Inefficiency parameters		Total	RA		QT	STE
Constant	δ_0	-16.052**	-8.896*		-4.136*	9.278
		(7.328)	(5.552)		(2.458)	(7.139)
Farm-size	δ_1	18.669***	24.993***		4.158***	7.447*
		(2.686)	(8.388)		(0.964)	(4.912)
Extension	δ_2	-10530***	-017.677**		-2.927***	- 3.601*
		(2.930)	(8.296)		(1.025)	(1.901)
Gender	δ_3	-4.524***	-9.078***		-2.114**	2.244*
		(1.563)	(2.694)		(0.982)	(1. 173)
Education	δ_4	0.954***	4.754***		-1.023**	-0. 526
		(0.362)	(1.798)		(0.429)	(0. 520)
Age	δ_5	-0.297**	-2.469***		-0.006***	0.141
		(0.099)	(0.941)		(0.0015)	(0.191)
Age square	δ_6	0.0005	0.026***		0.490***	-0.002
		(0.001)	(0.009)		(0.147)	(0.002)
Family size	δ_7	1.651***	4.046**		-1.140***	-0.984**
		(0. 588)	(1.840)		(0.436)	(0.664)
Credit	δ_8	3.488**	4.410***		2.771**	-3.604*
		(1.388)	(1.859)		(1.108)	(2.163)
Crops planted	δ_9	-3.135***	2.514		-2.904***	-6.818**
		(0.919)	(1.334)		(0. 646)	(3.211)
Sharecropped in ratio	δ_{10}	9.504***	22.151**		-4.538***	-6.948
		(2.851)	(6.922)		(0.810)	(2.706)
Variance parameters						
δ^2		55.144***	96.581**		6.294***	2.551**
		(16.652)	(43.165)		(1.438)	(5.806)
Γ		0.977***	0.994***		0.847***	0.883***
		(0.0077)	(0.003)		(0.042)	(0.053)
LL function		-1001.961	-340.912		-293.069	-288.697

***, ** and * are 1 *, 5% and 10% significant

Source; 2012/13 own computation from HARITA data

Therefore, the hypothesis of homogeneous technology for all farmers is rejected and metafrontier analysis is applied accordingly. In line to this fact, some variables included in the stochastic production frontier model as well as inefficiency effect model have mixed effects on the estimated production frontiers and inefficiency models. The variation of effects in these variables on the frontiers and inefficiencies across groupings is both in terms of significance level and sign.

As it is indicated in table 4.4; the variables labor, land and irrigation were found to be the most important factors affecting the level of production. Moreover, most of the classical (conventional) inputs included in the model demonstrated the expected sign. The variable oxen day and seed per hectare has negative coefficients for the pooled data and STE groups. But the effects of labor, land, irrigation and year dummy on production were found positive and significant. For the farmers in RA group land and labor respectively have negative insignificant and positive significant coefficients. Labor for the farmers in QT group, on the other hand, has unexpectedly negative sign and significant at 5 percent level of significance. This negative coefficient of labor can be justified due to the QT locality is one the most densely populated area in the region. The remaining coefficients in all frontiers have the expected sign suggesting a positive relationship between inputs and outputs. The stochastic frontier variables considered in this model include labor (X1), land (X2), seed (X3), oxen day (X4) and irrigation (X5). The variable time trend is also included in this model where as its coefficient suggests about technical change in production across years.

The distributional assumptions of the composite error term as measured by the estimated variance ($\sigma 2$), which is statistically significant at 5%, shows the goodness fit of the model and the correctness of the specified functional form. More specifically, the value of sigma squared measures the variation of output due to the variation in error terms of the composite error term. Gamma (γ), the variance of the non negative farm effects is significantly large proportion of the total variance of agricultural outputs. It accounts above 80 percent of the variation in total output for the data sets in all groups. This signifies there is huge level of inefficiency and thereby room for improvement of productivity with improvements of household level efficiency.

The coefficients of Cobb-Douglas stochastic production are interpreted using the elasticity concept, i.e., as the percentage change in output due to a unit percentage change in the input holding all other things constant. Except for RA group where labor is with the largest coefficient of elasticity, land explains the highest variations of the output. Adding all the coefficient of these variables in the frontier function we come up with the scale of the economy. The sum of elasticity coefficients in a given stochastic frontier function would result the scale of return in the production technology. In this study it is found the sum of elasticity coefficients for the three frontiers is greater than unity. Although it is not statistically tested if significantly different from one, it is 1.192 for the pooled data set, 1.329 for RA group, 1.902 for QT groups and 1.25 for STE groups. If the sum is greater than unity, it implies farmers are operating at increasing returns to scale, which is against our expectation. The first order coefficients of the time trend variable show estimates of the average annual rate of technical change (TC) (Wang et al, 2010). For this study time trend has positive coefficient (0.56, 1.14, 0.627 and 0.476 in pooled, RA, QT and STE groups respectively) for all frontiers and hence there is an improvement in TC.

4.3 Technical Efficiency and Technological gap ratios

After the data on agricultural production were extracted from the data collected by HARITA project, the analysis commence by estimation of groups-specific SPFs and pooled SPF revealing technical effects. It then proceeds to the meta-frontier analysis for estimating technology gap ratios and technical efficiency. The dependent variable in the frontier analysis is the value of agricultural production, which is preferred due to non-comparability, non additive nature of quantity measurements across different agricultural products of farm households under the study. These problems are thus, solved by valuing products using Ethiopian currency ‘Birr’ and add to a single variable-GVO.

Using the likelihood ratio (LR) test statistic for the null hypothesis that the group-specific frontiers are identical is 152. The LR test statistic follows a chi-square distribution with 20 degrees of freedom. Following that result, null hypothesis is rejected with a p-value less than 0.001 implying that the group-specific frontiers are not the same. Therefore, stochastic metafrontier function fitted to the data set. Table 4.5 provides average TE scores relative to the

group-specific stochastic frontiers, pooled frontier and metafrontier technologies as well as TGR scores of farmers both at individual and group levels for the production year of 2009 and 2010.

Table 4.5: Summary statistics of TE, TGR and TE estimates of farm households*

	Descriptive Statistics	Raya Azebo	Qolla Temben	S.T. Emba	Total
TE w.r.t SF	Obs	158	186	149	493
	Mean	.32265	.63794	.48531	.39587
	Std. Dev.	.22723	.14833	.18591	.18198
	Min	.00013	.00150	.00134	.00032
	Max	.85345	.86855	.77699	.819
	Variable	Raya Azebo	Qolla Temben	S.T. Emba	Total
TGR	Obs	158	186	149	493
	Mean	.54209	.57091	.21001	.45260
	Std. Dev.	.19314	.22315	.12419	.24689
	Min	.11375	.02349	.04479	.02349
	Max	1	1	1	1
	Variable	Raya Azebo	Qolla Temben	S.T. Emba	Total
TE* w.r.t MF	Obs	158	186	149	493
	Mean	.1765597	.36112	.09369	.22115
	Std. Dev.	.1484997	.15916	.05597	.17455
	Min	.000037	.00075	.00041	.00004
	Max	.7711485	.77829	.32596	.77829

Note; TE and TE* are group frontier and Metafrontier technical efficiencies

Source; Own computation of 2013 from HARITA data

TE scores relative to their respective location specific technology ranges from 0.00013 to 0.853, from 0.0015 to 0.869 and from 0.0013 to 0.777 for RA, QT and STE group farmers respectively. With regard to the mean TE score, QT has 0.64 suggesting they are producing 64 % of the maximum (ideal) output that can be produced using the same input and technological level. In other words, this output can be produced by 36% lower input level holding all other things constant. When we look at STE groups put at the second place in terms of their mean TE score, they produce 48.5% of the maximum producible output given the same level of technology. RA group farmers have lowest TE score (32 %) relative to their group frontier. This implies they can produce the same amount of output using inputs 67 % lower than they currently use under same technology level. In other words, on average smallholder farmers QT, STE and RA incur about 36, 51 and 67 percent loss in output respectively due to technical inefficiency. This implies that on average output can be increased by the amount of the loss while utilizing existing resources and technology if the inefficiency factors are fully addressed. In this data set, the highest

[4]variation (heterogeneity) of inefficiency is seen in RA group farmers with a standard deviation of 0.227 followed by S.T.E and QT farmers having standard deviations of 0.186 and 0.148 respectively.

When we come to the TGR estimates, it measures the proportion of the technology differential of each firm in a group, relative to the best technology in the industry. TGR measures assume that all groups have potential access to the best technology in the industry. It enables to estimate the extent to which productivity of a given DMU or group of DMUs could be increased if achieved the best given the inputs level at hand. Meaning that, given the input vector applied, it estimates the maximum output that could be produced by a DMU in a given group relative to the metafrontier output that is feasible using the metatechnology. Metafrontier is the boundary of input output sets available to each DMUs given the existing state of technology in the total sampled farmers and it envelops all restricted group frontiers. TGR score is less than or equal to 1, and a score of 1 represents that the farmer is applying the best technology available in the industry, agriculture here in our case.

The highest mean TGR is seen for QT group farmers and ranges from 0.023 to 1, where 1 is for those who are on the meta-technological frontier. In all location group frontiers, there is at least one farmer, but only one farmer in STE, on the metatechnological frontier output. This suggests that all group specific frontiers are tangent with the Metafrontier. This is an indication that it is possible to produce the maximum output represented by the metafrontier given the current state of environment. It is because some farmers in all groups are achieving the level of output potentially represented by MF given their current input vectors. Therefore, policy makers using different mechanisms to minimize the gap between farmers either through knowledge sharing within the groups or solving their constraints at household level, can help farmers achieve the highest possible output on MF given the current technology available in the industry. The minimum mean TGR score is observed in STE and this is because the land area is relatively too infertile to cultivate. The mean TGR for QT group is 0.571 followed by RA and STE groups respectively having TGR mean values of 0.542 and 0.21. The variation in TGR explained using standard deviation is higher QT, and the lowest is in STE group. This implies that currently

[4] For STE group there is only one farmer with TGR score of 1 that is producing output on the metafrontier.

given the inputs available at their disposal, the maximum output that can be produced relative to the potential output on MF is 57.1, 54.2 and 21 percent respectively for the three groups. From this it is possible infer that there is huge potential to increase agriculture productivity either through improving the production environment in all groups or designing programs for changing the structural and managerial aspects for improving the efficiency of farmers.

The highest variation of technology within groups is observed among QT farmers followed by RA and STE groups with a standard deviation of .223, 0.193 and 0.124 respectively. The equality of variances across groups is rejected at 1 percent of level of significance using Bartlett's test for equal variances. Looking mean TGR across groups using a pair wise analysis, the equality for TGR of QT and RA is not rejected while both are different from TGR score of STE group at 1 percent. For 2009 cropping year, TGR scores were 0.52, 0.52 and 0.24 for RA, QT and STE groups respectively. Whereas, for 2010 cropping they were 0.58, 0.64 and 0.16 for these groups respectively. An increase in TGR is observed among RA and QT groups as a decline is TGR score is seen in STE farmers. Overall mean TGR score for the whole groups is 0.45 (0.43 and 0.48 for 2009 and 2010 cropping years) where statistically significant improvement is observed.

Comparing TE of farmers where production frontiers vary in among locations (groups) is possible only if there is a common reference for all farmers upon on which their performance is estimated. Relative to group specific frontiers mean TE scores of QT, STE and RA are ranked respectively from higher to lower. For these TE scores the references, environment specific group frontiers, are different and performance comparison for farmers across environments is with different benchmarks is misleading. Taking the metafrontier technology as a reference, performance of farmers across different locations with varying technology can be compared. TE score relative to the metafrontier is the product of farmer's TE relative to his group frontier and TGR. Since the value of TGR do not exceed one, TE relative to metafrontier is less than or equal to TE score relative to the group frontiers.

The Metafrontier mean TE scores are 0.177, 0.361 and 0.094 respectively for RA, QT and STE group farmers. It ranges from the minimum of less than 0.001 for all groups to the maximum of 0.771, 0.778 and 0.326 for RA, QT and STE groups in order. The highest heterogeneity in TE* is

observed among QT farmers and the lowest is in STE farmers with standard deviation of 0.159 and 0.056 respectively. For the RA groups the standard deviation TE* is 0.148. Standard deviation measures indicate the efficiency differences across households in a given environment resulted from local level variations.

Based on TE*, QT group farmers take the lead with a mean score of 0.36 implying they actually produce 36 percent of the potential output represented by the MF, best technology available in the whole agriculture. Farmers in RA and STE groups with mean TE* scores of 0.18 and 0.09 respectively placed in rank. This suggests, on average the output produced by farmers in RA and STE is about 18 percent and 9 percent of the metafrontier output, the maximum output that can be produced by unrestricted technology in the industry. Comparatively low TGR and TE scores relative to metafrontier means farm households were operating far from the metafrontier. This deviation of TGR and TE measured with respect to the metafrontier function indicates that it is possible that agricultural TFP growth can be improved either through the improvement of TE or dissemination of technologies suitable to each specific environments.

4.4 Determinants of Technical inefficiency

The existence of household level technical inefficiency is verified using the values of gamma in group data sets ranging from the highest about 68 percent for RA and 36 percent for QT groups on average. There is also huge variation of technical inefficiency among farm households within and across groups. Moreover, efficiency varies with time. This variation of TE demands analyzing, to know what factors differentiate the farmers in attaining different levels of TE. Household and farm level as well as other socio-economic factors were included in the model. The overall significance using generalized LR test found 67.256, 54.728, 39.860 and 180.618 for RA, QT, STE groups and pooled data set respectively. They are greater than critical values at 5 percent significance level.

Following common steps in SFA, the variation in technical efficiencies among farm households can be explained in terms of the variation in the variables included in the model. Parameters' interpretation is carried out with regard to their effect on TE, which means that the estimated coefficients are analyzed as if they displayed the inverse sign. Variables included as inefficiency

variables, thus, with a negative coefficient means a positive effect on efficiency and productivity of farm households. The estimated coefficients are for farmers' age, education, access to extension services, access to credit, family size and farm size, number of crops sowed etc.

Table 4.5 Comparison of Mean TE and TE of the sampled households by year*

Statistics	Mean RA TE	Mean QT TE	Mean STE TE	Pooled TE	Mean TE*
year1	.268	.631	.467	.380	.198
year2	.396	.648	.510	.417	.254
Combined	.323	.638	.485	.396	.221
Diff	-.128	-.0167	-.042	-.037	-.056
Ho:	***	Accept	*	**	***

H_O: diff = mean (1) - mean (2) and Ho: diff = 0

***, ** and * are 1, 5 and 10 percent different

Source; own computation from HARITA data

In the analysis of the determinants of efficiency, the computed technical efficiencies were simultaneously modeled to depend on these identified variables. The coefficients with their corresponding standard errors of the estimated models are presented in Tables 4.4. The estimated coefficients of the explanatory variables in the model for the determinants of efficiency are of interest because they have important policy implications. The results show that most of the coefficients of the determinants of efficiency are significant. This means that the variables included as determinants of efficiency are very relevant in explaining the level of individual technical efficiency. It is found that, socio-economic factors, such as, household characteristics, plot characteristics etc affect household level technical efficiency. The technical efficiencies of smallholder maize farmers ranged from minimum of almost zero (see in appendix III) to the maximum of .853, .867 and .777 for RA, QT and STE groups respectively. Most of the inefficiency variables included in the model have different effects, either in magnitude or with respect to sign, on the technical inefficiency score of farm households in different environments.

The variable Extension service showed negative sign implying a positive and significant effect on household level technical efficiency. The rational to include this variable in the efficiency effect estimation is that people who have access to extension services are expected to have better information about scientific way of farm production so that they would become more efficient in their farming activity. In the same manner, the effect of access to extension service was

significant at one percent for the pooled data set and QT Farmers while significant at 5 and 10 percent for RA and STE farmers respectively. Age of the household head found to be positively and significantly affecting technical efficiency for RA, QT and total data set. These results are in line with the premise that increases in human capital, either through training, experience or counseling etc, enable rural households to get better in resource utilization and thereby achieve higher farm productivity. Age of the household head can be a proxy for the years of experience in agriculture which can have a significant impact on efficiency. Thus, inefficiency will decline with the increase in the commutative knowledge obtained from years of experience in agriculture. This result is contradicts the finding of Kalirajan and Shand (1988) that state extension contact has no significant relationship to technical inefficiency as extension agents do not have new information to equip farmers. In Ethiopia Alene (2003), Alene et al. (2005) Alemu et al. (2009) found insignificant effect of extension. On the other hand, Yohannes and Garth (1993), Gebregziabher (2013) found positive significant effect of extension service on TE. In contrary, Haji (2006) as cited in Gebregziabher (2013) found negative effect of extension services on TE.

For all datasets except STE groups, gender of the household head present positive and significant effects, on TE telling that male-headed households are more efficient than their female counterparts. Gonzalez (2004) contend that lower levels of efficiency among female headed households could stem from gender inequities in rural areas, where women have more difficult access to capital and/or other financial services. Moreover, it could also result from unmeasured outputs generated by females in the household. Similarly, in developing countries including Ethiopia, female household-heads are not only in charge of their family business. They are also responsible for taking care of basic household needs such as; child rearing and care, cooking, cleaning, etc. Since such activities of women are difficult to quantify but compete for their time and effort, care should be made for comparative analysis. Some gender studies show that females' role in GDP which is 1/3 of GDP is ignored. Thus, female headed households may not be less efficient but they allocate some time for home goods. To verify this hypothesis here in with, in depth intra-household information is necessitated, which is not on hand for this study. Gender in STE groups is found have negative technical inefficiency effect implying women headed household are more efficient compared to male headed households. Moreover, this is clearly an area that merits

further research as it is inconsistent with findings of many researches. May be the groups have small land size under cultivation and that may not require laborious efforts.

The estimated parameters of Credit, Age, Education and sharecropped in land for the farmers in STE group are not statistically different from zero. Conversely, farm households in QT group were found with negative coefficient of sharecropped in land implies they are working efficiently on the sharecropped land. The estimated coefficient is significant at 1 percent. In contrary to that, for pooled farmers and RA group farmers the variable sharecropped in ratio has positive sign suggesting that farmers are working efficiently on their own land as compared to sharecropped in land.

In this study the effect of education on technical inefficiency farm households is found mixed way. Sometimes, in developing countries Education do not has clear effect on performance of the agricultural sector (Temesgen B. and Ayalneh B., 2005). Education may not be important (relevant) to agricultural productivity which is mainly traditional not equipped with modern technology rather based on a common practice. To a certain extent education of working family members may be accompanied with a competing time for agricultural activities and thereby brought a decline in agricultural productivity. The relationship between the household level inefficiency of farmers and average education of the household was found negative for QT farmers, while positive for RA farmers. For STE farmers although not statistically significant it is seen to be negative. In line with these different findings Kalirajan and Shand (1988); Parikh and Shah (1995); Sharif and Dar (1996); Xu and Jeffery (1998); Demeke (1989); Asfaw and Admassie (1996) and Hailu et al. (1998) for have found a negative relationship between inefficiency and household education. On the other hand, Sriboonchitta and Wiboonpongse (2000) found a positive relationship between education and technical inefficiency of rice production in Thailand, while Wharton (1965) was unable to see a meaningful relationship between agricultural production and education level of farmers, and suggested that the of education in the early stages of agricultural development has not certain contribution (Temesgen B. and Ayalneh B., 2005). The empirical works from Dadzie and Dasmani (2010); Alemu et al (2009) and Marinda et al. (2006) found positive effect of education on technical efficiency.

Similarly, the study go on showing that credit have different relations with the level of technical inefficiency of the farm household in different groups. It is found in this study that, credit constraint has positive relation with the level of technical inefficiency for the pooled, RA and QT data sets while for STE it is found to be negative and statistically significant at 10 percent level of significance. Those credit constrained farm households could face a liquidity constraint to purchase productivity enhancing inputs necessary for agriculture when needed and undertake activities on time. On the other hand, in this study it is found that credit constraint has negative relation with the level of technical inefficiency and is statistically significant at 10 percent. This could be resulted due to the reason that farmers who have better access of credit might not use their money appropriately or might use for non agricultural activity. Moreover, they may not demand credit for agriculture rather for other reasons. More precisely, those who accessed credit could engage in nonfarm activity since the land in the study area is too small in size and poor in quality as compared to other locations where the result is found to be opposite in sign. Therefore, migration of active work force in the family members to non-farm sector could leave household to be less efficient in farm productivity. Liu and Zhuang (2000), based on Mukesh and Ashok (1989) argue that credit can mitigate consumption risk and thus encourage investment by risk-averse small farmers and hence promote technical efficiency. Saldias and Taubadel (2012) found positive relationship between volume of credit and TE whereas, Battese and Broca (1997) in their examination of the importance of the choice of functional forms in parametric efficiency analysis found a negative relation between credit constraints and efficiency. Liu (2005) and Hazarika and Alwang (2003) found no significant relation as Okike et al (2001) in contrary reported negative relation between credit and efficiency. Another reason could be those who use borrowed money could tend to be risk averse due to peer pressure but those without credit could take risk since they are using their own money.

Family size in RA has a positive and significance effect on inefficiency while for QT and STE farmers; family size is associated with inefficiency negatively. The effect of family size on QT and STE farmers' efficiency is mainly justified on the ground that those farmers with larger family sizes can better manage their crops. This was again based on the assumption that there is strong correlation between the work force (i.e. economically active members of the family) and

family size. This finding is in line with the findings of Demeke (1989). For the case of RA farmers it could be a case of the random error resulted from drought, i.e. intensity of labor used could have positive effect on productivity and efficiency only if it is accompanied by adequate rainfall. On the other hand, it can be justified Drudgery averse hypothesis. It well stated that peasant production was orientated towards utility maximization (use value), work would only be intensified until the gains from any further increases in work input would be outweighed by its drudgery. Thus, once a peasant household had done enough work to ensure an acceptable standard of consumption for the family as a whole, it would not work any harder. The amount of work done by the individual working members of a household will be inversely related to the number of dependent consumers they have to support. The higher the ratio of non-working children to workers there is in a household, the harder the productive members will have to work. But it yet looked for further research.

Farm size is found positively related with technically inefficiency of farm households in all groups. It was positive and statistically significant at 5% for RA and QT farmers and at10 % for STE farmers. Therefore, positive association of land size with technical inefficiency of farm households in all areas implying that relatively small land holders are better managing their farm and are efficient compared to the larger counterparts. The result obtained in this study is line with Schultz (1964) and Barrett (1996) who found inverse relationship between farm size and productivity. This fact is oft-observed pattern in the rural areas of less developed countries and that is why many researchers found that small farms are often cultivated more intensively than large farms; more labour per unit area is used on small farms, and yields are larger on these smaller farms. In contrary to this result, Onyenweaku, et al. (2004), Onyenweaku and Effiong (2005) and Flinn and Ali (1986) found negative relationship and Kalirajan and Flinn (1983), Huang and Bagi (1984) Lingard, et al., (1983), Kalirajan, (1991), Bravo-Ureta and Evenson (1994) and Bravo-Ureta and Pinheiro (1994) found no significant relationship between farm size and technical inefficiency.

Moreover, the number of crops planted by the farmer is negatively correlated with the inefficiency of the farm households in all environments. This can be argued diversification of production and thereby minimize risk of crop failure. In addition to that, the plot on their hand

could be convenient for planting different products compatible to the soil type. This result is found to be consistent with the findings of Solis et al. (2008) in his input oriented technical efficiency analysis. He found positive relationship between output diversification and productivity.

CHAPTER FIVE

CONCLUSIONS AND POLICY HIGHLIGHTS

For this study panel data set of two cropping periods (2009 and 2010) collected by HARITA project in collaboration with Mekelle University, Department of Economics, was used for analyzing performance of farm households. Metafrontier framework with stochastic frontier model based on a Cobb Douglas production functional form was applied. Following the LR test of technology homogeneity across environmental groups and found they are different, the researcher estimated three Environmental stochastic group frontiers for each environment. A stochastic metafrontier production function was then fitted to these location based Environmental group frontiers to undertake performance comparisons across farm households in different groups and estimate EMTR. The data was collected in drought prone areas of Tigray regional state (Raya Azebo, Qolla Temben and Saesie Tsaeda Emba). Therefore, it could be necessary to undertake further investigation to have conclusive results for the region and the country as a whole.

5.1 CONCLUSIONS

To estimate the production frontier, conventional inputs consisting of cultivated area, labor, seeds, oxen day and irrigation were included. Household and Farm-specific variables such as age, gender, education, household size, land size, sharecropping and number of crops planted have varied effects on household-level inefficiencies among the three environments. The selection and inclusion these conventional and non-conventional inputs are based on economic theories extracted from reviewing different literatures.

From this analysis production possibilities and technologies of farm households in different environments were found different as farmers could employ different production technologies suitable to their environmental conditions. Consequently, using technical inefficiency effect model, environment specific stochastic frontiers for the three groups and the pooled sample set are estimated with Coelli's (1996) FRONTIER4.1 software. On the other hand, the researcher followed O'Donnell's et al. (2008) procedure to construct Metafrontier production curve using

SHAZAM software. Technical efficiency of farm households were then measured relative to their group specific environmental frontiers whereas, EMTR in Agriculture for farmers in the three environments are estimated relative to the metafrontier. Metafrontier function is also used to compare mean TE* and TGR estimates- performance of farmers- across environments. In this study, it was found mean TE score for the pooled sample is about 40 percent and relative to their group specific frontiers mean TE for RA, QT and STE group farmers are 32.3, 63.8 and 48.5 respectively, indicating the existence of massive technical inefficiency in farm households. Whereas, TE scores relative to MF for these groups are 17.6, 36.1 and 9.4 percent respectively.

Therefore, agricultural production can increase by the amount of inefficiency, more than 50 percent on average in this case, without increasing the amount of inputs employed for agricultural practices. In other words, inputs can be reduced by more than 50 percent without changing the amount of agricultural output produced if inefficiency problems are adequately solved.

Group specific TE scores are far lower than the metafrontier TE scores as there is huge deviation of TGR from MF output. On the other hand, the existence of TGR equals one in all environments, implies that there is a possibility to reach the highest attainable output represented on the metafrontier through disseminating technologies suitable in a particular area coupled with training and information services. Mean TEs and EMTRs largely differ across environments implying that farmers are incapable to adapt their management practices so as to solve environmental constraints they face and thereby exploit the maximum possible. Some inefficiency factors are found to differ in their effect on technical efficiency of farmers in different localities (groups) either in sign or magnitude.

5.2 POLICY HIGHLIGHTS

The fact that there is large technical inefficiency of farm households among all environmental groups suggest that there is a scope for government agencies or policy makers to reduce food insecurity in the county by appropriately tackling sources of technical inefficiencies. Therefore, in countries like Ethiopia where modern agricultural inputs are too scarce it is better to focus on taking efficiency enhancing measures to reduce the problem of food insecurity.

Access to extension service, Age of the household head (proxy experience) and Crop diversification were found with their technical inefficiency reduction effects for all households in the three environments. Therefore, policy makers can play a task in reducing technical inefficiency by extending the outreach as well as intensity of extension services in the country to deliver through training, consultancy and follow up services for the farmers. Moreover, this activity of the government and policy makers can be supported through sharing experience among farmers within and across groups in enhancing technical efficiencies in particular and technological production in general.

Diversification of crops planted by the farmer has also negative technical inefficiency effect and this able the farmer to produce output closer at the frontier output. This crop diversification could also absorb excess labor in rural households. Moreover, in production environment where climatic and rainfall variations are too high like study areas for this research, farmers can minimize the risk of crops failure by diversifying their crops. Diversification can also help farmers to have better access for commercializing their production activities. This market linkage can also exert its own spillover effect on their production. Therefore, crop diversification due to its commercialization effect, as a risk pooling strategy or by absorbing excess labor, could help in enhancing technical efficiency of farmers in their agricultural production.

In dealing with the productivity and efficiency of farmers across these three geographical locations it is found their production possibility varies perhaps due to the difference in the resources; environmental, technological, physical and/or human resources etc embodied in their working environment. Consequently, a need arises to use metafrontier framework for measuring and comparing performances of farmers with heterogeneous technology. This finding gives insight for further related researches to consider the possibility of technology variation across the decision making units under their study. This will help to clearly understand and pinpoint the productivity effect of technical inefficiency and technological gap among groups or units.

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Appendix I

5.1 Mean and variance analysis over groups and overtime

5.1.1 Pair wise comparison across geographic locations

5.1.1.a oneway tgr envronment, tabulate bonferroni

```
            |           Summary of mtr
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .54208684   .19313523         158
  qolla tem |     .570912   .22315391         186
  sasie tsa |   .21000709   .12419022         149
------------+------------------------------------
      Total |   .45259718   .24688781         493

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      12.6376718      2   6.31883592    178.44     0.0000
 Within groups      17.3514953    490   .035411215
------------------------------------------------------------------------
    Total           29.9891671    492   .060953592

Bartlett's test for equal variances:  chi2(2) =  51.6316  Prob>chi2 = 0.000

                       Comparison of mtr by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .028825
         |      0.472
         |
sasie ts |    -.33208   -.360905
         |      0.000      0.000
```

5.1.1 .b oneway tgr envronment if timep==1, tabulate bonferroni

```
            |           Summary of mtr
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .51667929   .20662885          91
  qolla tem |   .52027572   .23361769         108
  sasie tsa |   .24186048   .13567592          88
------------+------------------------------------
      Total |   .43376765   .23621834         287

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      4.67469445      2   2.33734723     58.83     0.0000
 Within groups      11.2838488    284   .039731862
------------------------------------------------------------------------
    Total           15.9585433    286   .055799102
```

```
Bartlett's test for equal variances:  chi2(2) =  26.3672  Prob>chi2 = 0.000

                        Comparison of mtr by envronment
                                 (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .003596
         |      1.000
         |
sasie ts |   -.274819   -.278415
         |      0.000      0.000
```

5.1.1.c oneway tgr envronment if timep==2, tabulate bonferroni

```
             |           Summary of mtr
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |    .5765956   .16855742          67
  qolla tem |   .64102378   .18768821          78
  sasie tsa |   .16405465   .08784889          61
------------+------------------------------------
      Total |   .47883056   .25933405         206

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups       8.7364204      2    4.3682102    175.57     0.0000
 Within groups      5.05068008    203   .024880197
------------------------------------------------------------------------
    Total           13.7871005    205   .067254149

Bartlett's test for equal variances:  chi2(2) =  34.4707  Prob>chi2 = 0.000

                        Comparison of mtr by envronment
                                 (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .064428
         |      0.045
         |
sasie ts |   -.412541   -.476969
         |      0.000      0.000
```

5.1.1. d oneway metaefficiency envronment, tabulate bonferroni

```
             |           Summary of mte
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .17655967   .14849973         158
  qolla tem |    .3611186   .15915541         186
  sasie tsa |   .09369206   .05597112         149
------------+------------------------------------
      Total |   .22114524   .17455327         493

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
```

```
Between groups      6.37869949      2   3.18934975    181.47     0.0000
 Within groups      8.61197254    490   .017575454
---------------------------------------------------------------------------
    Total            14.990672    492   .030468846

Bartlett's test for equal variances:  chi2(2) = 151.5795  Prob>chi2 = 0.000

                       Comparison of mte by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .184559
         |      0.000
         |
sasie ts |   -.082868   -.267427
         |      0.000      0.000
```

5.1.1 .e oneway metaefficiency envronment if timep==1, tabulate bonferroni

```
            |           Summary of mte
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .14143817   .15769645          91
  qolla tem |      .32217   .16118986         108
  sasie tsa |   .10275514   .05692687          88
------------+------------------------------------
      Total |   .19758776   .16781933         287

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
---------------------------------------------------------------------------
Between groups      2.75454593      2   1.37727297     73.80     0.0000
 Within groups      5.30016589    284   .018662556
---------------------------------------------------------------------------
    Total           8.05471182    286   .028163328

Bartlett's test for equal variances:  chi2(2) =  90.6432  Prob>chi2 = 0.000

                       Comparison of mte by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .180732
         |      0.000
         |
sasie ts |   -.038683   -.219415
         |      0.178      0.000
```

5.1.1. f oneway metaefficiency envronment if timep==2, tabulate bonferroni

```
            |           Summary of mte
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .22426199   .12056345          67
  qolla tem |   .41504742   .14028523          78
  sasie tsa |   .08061744    .0522901          61
------------+------------------------------------
      Total |   .25396561   .17881438         206

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      3.91603261      2    1.9580163    150.63     0.0000
 Within groups      2.63875706    203   .012998803
------------------------------------------------------------------------
    Total           6.55478967    205   .031974584

Bartlett's test for equal variances:  chi2(2) =  53.8718  Prob>chi2 = 0.000

                       Comparison of mte by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .190785
         |      0.000
         |
sasie ts |   -.143645    -.33443
         |      0.000      0.000
```

5.1.1. g oneway effestpool envronment, tabulate bonferroni

```
            |        Summary of effestpool
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .34668272   .20996848         158
  qolla tem |   .42642279   .14005162         186
  sasie tsa |    .4098447   .18666126         149
------------+------------------------------------
      Total |   .39585673   .18197183         493
                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      .584987941      2   .292493971      9.12     0.0001
 Within groups      15.7069757    490   .032055052
------------------------------------------------------------------------
    Total           16.2919636    492   .033113747

Bartlett's test for equal variances:  chi2(2) =  28.4146  Prob>chi2 = 0.000

                    Comparison of effestpool by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |     .07974
         |      0.000
         |
sasie ts |    .063162   -.016578
         |      0.006      1.000
```

5.1.1 .h oneway effestpool envronment if timep==1, tabulate bonferroni

```
            |        Summary of effestpool
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .26554381   .22345961          91
  qolla tem |    .4488763   .15106688         108
  sasie tsa |   .41495932   .18581427          88
------------+------------------------------------
      Total |   .38034685   .20270696         287

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      1.81198088      2   .905990439     25.89     0.0000
 Within groups      9.93979069    284   .034999263
------------------------------------------------------------------------
    Total           11.7517716    286    .04109011

Bartlett's test for equal variances:  chi2(2) =  14.8846  Prob>chi2 = 0.001

                    Comparison of effestpool by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .183332
         |      0.000
         |
sasie ts |    .149416   -.033917
         |      0.000      0.623
```

5.1.1 .i oneway effestpool envronment if timep==2, tabulate bonferroni

```
            |        Summary of effestpool
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |    .4568863   .12399536          67
  qolla tem |   .39533333   .11716152          78
  sasie tsa |   .40246623   .18917417          61
------------+------------------------------------
      Total |   .41746515   .14608661         206
                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      .156048578      2   .078024289      3.75     0.0251
 Within groups      4.21891751    203   .020782845
------------------------------------------------------------------------
    Total           4.37496609    205   .021341298

Bartlett's test for equal variances:  chi2(2) =  19.0957  Prob>chi2 = 0.000

                    Comparison of effestpool by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |   -.061553
         |      0.033
         |
sasie ts |    -.05442    .007133
         |      0.102      1.000
```

5.1.1.j oneway efficiency envronment, tabulate bonferroni

```
            |        Summary of efficiency
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .32265288   .22723029         158
  qolla tem |    .6379376   .14832653         186
  sasie tsa |   .48530797   .18590549         149
------------+------------------------------------
      Total |   .49076356   .22895185         493

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      8.49850123      2   4.24925061    120.41     0.0000
 Within groups      17.2916224    490   .035289025
------------------------------------------------------------------------
    Total           25.7901237    492   .052418951

Bartlett's test for equal variances:  chi2(2) =  30.6589  Prob>chi2 = 0.000

                    Comparison of efficiency by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .315285
         |      0.000
         |
sasie ts |    .162655    -.15263
         |      0.000      0.000
```

5.1.1 .k oneway efficiency envronment if timep==1, tabulate bonferroni

```
            |        Summary of efficiency
 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |    .2684325   .25117865          91
  qolla tem |   .63092804   .16345333         108
  sasie tsa |   .46792747   .19073394          88
------------+------------------------------------
      Total |   .46601116   .25220671         287
                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      6.49005821      2   3.24502911     78.76     0.0000
 Within groups      11.7018934    284    .04120385
------------------------------------------------------------------------
    Total           18.1919516    286   .063608222

Bartlett's test for equal variances:  chi2(2) =  18.7571  Prob>chi2 = 0.000

                    Comparison of efficiency by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .362496
         |      0.000
         |
sasie ts |    .199495   -.163001
         |      0.000      0.000
```

5.1.1.l oneway efficiency envronment if timep==2, tabulate bonferroni

```
            |        Summary of efficiency

 envronment |        Mean   Std. Dev.       Freq.
------------+------------------------------------
  raya azeb |   .39629549   .16502657          67
  qolla tem |   .64764315   .12477348          78
  sasie tsa |   .51038147    .1772504          61
------------+------------------------------------
      Total |   .52524871   .18711353         206

                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      2.29609269      2   1.14804634     47.74     0.0000
 Within groups      4.88125944    203   .024045613
------------------------------------------------------------------------
    Total           7.17735213    205   .035011474

Bartlett's test for equal variances:  chi2(2) =   9.1492  Prob>chi2 = 0.010

                    Comparison of efficiency by envronment
                                (Bonferroni)
Row Mean-|
Col Mean |   raya aze   qolla te
---------+----------------------
qolla te |    .251348
         |      0.000
         |
sasie ts |    .114086   -.137262
         |      0.000      0.000
```

5.1.2 Mean and variance comparisons over time

```
. ttest metafrontierefficiency, by( timep )

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |     287    .1975878    .0099061    .1678193    .1780897    .2170858
    2010 |     206    .2539656    .0124586    .1788144    .2294022     .278529
---------+--------------------------------------------------------------------
combined |     493    .2211452    .0078615    .1745533     .205699    .2365915
---------+--------------------------------------------------------------------
    diff |           -.0563779    .0157516               -.0873268   -.0254289
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -3.5792
Ho: diff = 0                                     degrees of freedom =      491

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0002         Pr(|T| > |t|) = 0.0004          Pr(T > t) = 0.9998
```

```
. ttest  tgrall, by( timep )

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |     287    .4337676    .0139435    .2362183    .4063227    .4612126
    2010 |     206    .4788306    .0180687     .259334    .4432063    .5144548
---------+--------------------------------------------------------------------
combined |     493    .4525972    .0111193    .2468878    .4307501    .4744443
---------+--------------------------------------------------------------------
    diff |           -.0450629     .022476               -.089224   -.0009018
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -2.0049
Ho: diff = 0                                     degrees of freedom =      491

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0228         Pr(|T| > |t|) = 0.0455          Pr(T > t) = 0.9772

. ttest   effestpool, by( timep )

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |     287    .3803469    .0119654     .202707    .3567954    .4038983
    2010 |     206    .4174652    .0101783    .1460866    .3973975    .4375328
---------+--------------------------------------------------------------------
combined |     493    .3958567    .0081956    .1819718     .379754    .4119594
---------+--------------------------------------------------------------------
    diff |           -.0371183    .0165494               -.0696346    -.004602
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -2.2429
Ho: diff = 0                                     degrees of freedom =      491

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0127         Pr(|T| > |t|) = 0.0253          Pr(T > t) = 0.9873

. ttest    pooledefficiency, by( timep )

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |     287    .4660112    .0148873    .2522067    .4367086    .4953137
    2010 |     206    .5252487    .0130368    .1871135    .4995453    .5509521
---------+--------------------------------------------------------------------
combined |     493    .4907636    .0103115    .2289519    .4705036    .5110235
---------+--------------------------------------------------------------------
    diff |           -.0592375    .0207569               -.1000208   -.0184542
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -2.8539
Ho: diff = 0                                     degrees of freedom =      491

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0023         Pr(|T| > |t|) = 0.0045          Pr(T > t) = 0.9977

. ttest mtrr, ( time)
option ( not allowed
r(198);
```

```
. ttest TGRrayaazebo, by( time)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |      91    .5166793    .0216606    .2066289    .4736467    .5597118
    2010 |      67    .5765956    .0205926    .1685574    .5354812      .61771
---------+--------------------------------------------------------------------
combined |     158    .5420868     .015365    .1931352     .511738    .5724356
---------+--------------------------------------------------------------------
    diff |           -.0599163    .0308192               -.1207931    .0009604
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -1.9441
Ho: diff = 0                                     degrees of freedom =      156

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0268         Pr(|T| > |t|) = 0.0537          Pr(T > t) = 0.9732

. ttest mfefficiencyraya, by( time)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |      91    .1414382    .0165311    .1576965    .1085963      .17428
    2010 |      67     .224262    .0147292    .1205634    .1948543    .2536697
---------+--------------------------------------------------------------------
combined |     158    .1765597     .011814    .1484997    .1532248    .1998946
---------+--------------------------------------------------------------------
    diff |           -.0828238    .0230469                -.128348   -.0372996
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -3.5937
Ho: diff = 0                                     degrees of freedom =      156

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0002         Pr(|T| > |t|) = 0.0004          Pr(T > t) = 0.9998

. ttest   sfeffestraya, by( time)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |      91    .2684325    .0263307    .2511786     .216122     .320743
    2010 |      67    .3962955    .0201612    .1650266    .3560423    .4365486
---------+--------------------------------------------------------------------
combined |     158    .3226529    .0180775    .2272303    .2869465    .3583593
---------+--------------------------------------------------------------------
    diff |            -.127863    .0352396               -.1974713   -.0582546
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -3.6284
Ho: diff = 0                                     degrees of freedom =      156

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0002         Pr(|T| > |t|) = 0.0004          Pr(T > t) = 0.9998
```

```
. ttest    TGRtemben, by( timet)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |     108    .5202757    .0224799    .2336177     .475712    .5648394
    2010 |      78    .6410238    .0212515    .1876882    .5987066    .6833409
---------+--------------------------------------------------------------------
combined |     186     .570912    .0163624    .2231539     .538631     .603193
---------+--------------------------------------------------------------------
    diff |           -.1207481    .0320352               -.1839517   -.0575444
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -3.7692
Ho: diff = 0                                     degrees of freedom =      184

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0001         Pr(|T| > |t|) = 0.0002          Pr(T > t) = 0.9999

. ttest     sfeffesttemben, by( timet)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |     108     .630928    .0157283    .1634533    .5997485    .6621076
    2010 |      78    .6476431    .0141278    .1247735    .6195111    .6757752
---------+--------------------------------------------------------------------
combined |     186    .6379376    .0108758    .1483265     .616481    .6593942
---------+--------------------------------------------------------------------
    diff |           -.0167151    .0220657               -.0602493    .0268191
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -0.7575
Ho: diff = 0                                     degrees of freedom =      184

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.2249         Pr(|T| > |t|) = 0.4497          Pr(T > t) = 0.7751

. ttest      mfefficiencytemben, by( timet)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |     108      .32217    .0155105    .1611899    .2914222    .3529178
    2010 |      78    .4150474    .0158842    .1402852     .383418    .4466769
---------+--------------------------------------------------------------------
combined |     186    .3611186    .0116698    .1591554    .3380955    .3841417
---------+--------------------------------------------------------------------
    diff |           -.0928774    .0227035               -.1376701   -.0480848
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -4.0909
Ho: diff = 0                                     degrees of freedom =      184

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0001          Pr(T > t) = 1.0000
```

```
. ttest mtrsaesietsaedaE, by( times)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |      88    .2418605    .0144631    .1356759    .2131135    .2706075
    2010 |      61    .1640547    .0112479    .0878489    .1415555    .1865538
---------+--------------------------------------------------------------------
combined |     149    .2100071    .0101741    .1241902    .1899019    .2301123
---------+--------------------------------------------------------------------
    diff |            .0778058    .0197442                .0387867     .116825
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =   3.9407
Ho: diff = 0                                     degrees of freedom =      147

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9999         Pr(|T| > |t|) = 0.0001          Pr(T > t) = 0.0001
. ttest   effsaesieTsaedaem, by( times)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |      88    .4679275    .0203323    .1907339    .4275148    .5083401
    2010 |      61    .5103815    .0226946    .1772504    .4649855    .5557774
---------+--------------------------------------------------------------------
combined |     149     .485308      .01523    .1859055    .4552117    .5154043
---------+--------------------------------------------------------------------
    diff |           -.042454      .03088               -.1034801     .018572
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =  -1.3748
Ho: diff = 0                                     degrees of freedom =      147

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0856         Pr(|T| > |t|) = 0.1713          Pr(T > t) = 0.9144

. ttest   mfeficiencysaesie, by( times)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    2009 |      88    .1027551    .0060684    .0569269    .0906935    .1148168
    2010 |      61    .0806174    .0066951    .0522901    .0672253    .0940096
---------+--------------------------------------------------------------------
combined |     149    .0936921    .0045853    .0559711    .0846309    .1027532
---------+--------------------------------------------------------------------
    diff |            .0221377    .0091768                .0040022    .0402732
------------------------------------------------------------------------------
    diff = mean(2009) - mean(2010)                                t =   2.4123
Ho: diff = 0                                     degrees of freedom =      147

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9915         Pr(|T| > |t|) = 0.0171          Pr(T > t) = 0.0085
```

5.2 Summary statistics of TE and TE* and MTR

sum mtrr effestray mter mtrt effesttem mtet mtrs effsae mtes effestpool aggrmtr aggmte

	Variable	Obs	Mean	Std. Dev.	Min	Max
RA	mtr	158	.5420868	.1931352	.1137515	1
	eff	158	.3226529	.2272303	.0001279	.8534529
	mte	158	.1765597	.1484997	.000037	.7711485
QT	mtrt	186	.570912	.2231539	.0234894	1
	eff	186	.6379376	.1483265	.0014999	.8685486
	mte	186	.3611186	.1591554	.0007476	.7782879
STE	mtr	149	.2100071	.1241902	.0447917	1
	eff	149	.485308	.1859055	.0013422	.776994
	mtes	149	.0936921	.0559711	.0004067	.3259645
effestpool		493	.3958567	.1819718	.000322	.819
aggrmtr		493	.4525972	.2468878	.0234894	1
aggmte		493	.2211452	.1745533	.000037	.7782879

Appendix II

5.3 Multi-collinearity, heterosckedasticity and omitted variable test

i. Translog Functional Form for the polled data

.

```
reg output labor land oxen seed irregation laboursq laborland laboroxen laborirreg
laborseed landsqrs landsoxen landsirreg landseeds oxensqr oxenirregt oxenseeds
irregseeds s
> eedsqr year

      Source |       SS       df       MS              Number of obs =     496
-------------+------------------------------           F( 20,   475) =    6.22
       Model |  585.843869    20  29.2921934           Prob > F      =  0.0000
    Residual |  2237.28813   475  4.71008028           R-squared     =  0.2075
-------------+------------------------------           Adj R-squared =  0.1741
       Total |    2823.132   495  5.70329697           Root MSE      =  2.1703

------------------------------------------------------------------------------
      output |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       labor |  -8.329655   17.87245    -0.47   0.641    -43.44851     26.7892
        land |   1.350162   13.30238     0.10   0.919    -24.78862    27.48894
        oxen |  -4.745201   6.178239    -0.77   0.443    -16.88526    7.394858
        seed |  -.9587116   9.646285    -0.10   0.921    -19.91338    17.99596
  irregation |   1.427072   1.668804     0.86   0.393     -1.85208    4.706224
    laboursq |    .933854   10.63079     0.09   0.930    -19.95534    21.82305
   laborland |   2.057277   3.741064     0.55   0.583    -5.293806    9.408359
   laboroxen |   1.375088   .6125694     2.24   0.025     .1714065    2.578769
  laborirreg |  -.6859345   .4876687    -1.41   0.160    -1.644189    .2723203
   laborseed |   4.354012   9.518596     0.46   0.648    -14.34975    23.05778
    landsqrs |  -1.508685   4.001724    -0.38   0.706    -9.371956    6.354587
   landsoxen |  -.7843971   .6762736    -1.16   0.247    -2.113255    .5444608
  landsirreg |   2.166222   .6865377     3.16   0.002     .8171959    3.515249
   landseeds |  -1.158719   2.669837    -0.43   0.664     -6.40487    4.087432
     oxensqr |   2.085572   2.771938     0.75   0.452    -3.361206    7.532349
  oxenirregt |   .2988795   .3364537     0.89   0.375    -.3622422    .9600013
   oxenseeds |  -.7699476   .4576182    -1.68   0.093    -1.669154    .1292589
```

```
  irregseeds |  -.0419121     .24996    -0.17   0.867    -.5330762    .4492521
     seedsqr |  -.8157279   8.829319    -0.09   0.926    -18.16508    16.53363
        year |   1.225802   .2039224     6.01   0.000     .8251008    1.626504
       _cons |   4.371766   6.961719     0.63   0.530    -9.307809    18.05134
------------------------------------------------------------------------------

. vif
    Variable |       VIF       1/VIF
-------------+----------------------
     seedsqr |  29908.98    0.000033
    laboursq |  28571.82    0.000035
   laborseed |  19262.34    0.000052
       labor |  19214.92    0.000052
        seed |   8673.67    0.000115
        oxen |   4495.53    0.000222
     oxensqr |   3737.84    0.000268
        land |   2795.44    0.000358
   laborland |   2680.99    0.000373
   landseeds |   1497.31    0.000668
    landsqrs |   1049.01    0.000953
   laboroxen |    201.98    0.004951
   oxenseeds |    140.43    0.007121
   landsoxen |    102.84    0.009724
  laborirreg |    101.31    0.009871
  irregation |     66.25    0.015095
  irregseeds |     41.80    0.023925
  oxenirregt |     26.86    0.037235
  landsirreg |      8.46    0.118243
        year |      1.07    0.936595
-------------+----------------------
    Mean VIF |   6128.94

. ovtest

Ramsey RESET test using powers of the fitted values of output
       Ho:  model has no omitted variables
                 F(3, 472) =      7.44
                  Prob > F =      0.0001
```

ii. Cobb Douglas functional form for the pooled data

```
. reg output labor land oxen seed irregation year

      Source |       SS       df       MS              Number of obs =     496
-------------+------------------------------           F(  6,   489) =   15.19
       Model |  443.594803     6  73.9324672           Prob > F      =  0.0000
    Residual |   2379.5372   489  4.86612924           R-squared     =  0.1571
-------------+------------------------------           Adj R-squared =  0.1468
       Total |    2823.132   495  5.70329697           Root MSE      =  2.2059

------------------------------------------------------------------------------
```

```
      output |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       labor |   1.007295   .2244812     4.49   0.000     .5662286    1.448362
        land |  -.6891839   .3271095    -2.11   0.036    -1.331897   -.0464702
        oxen |  -.3171129   .1484839    -2.14   0.033    -.6088581   -.0253678
        seed |  -.1062239   .1169015    -0.91   0.364    -.3359151    .1234673
  irregation |   .9126085   .2144526     4.26   0.000     .4912462    1.333971
        year |   1.235394   .2044687     6.04   0.000     .8336479    1.637139
       _cons |   3.724447   .7790291     4.78   0.000      2.19379    5.255105
------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF
-------------+----------------------
       labor |      2.93    0.340820
        oxen |      2.51    0.397874
        land |      1.64    0.611192
        seed |      1.23    0.811022
  irregation |      1.06    0.944329
        year |      1.04    0.962462
-------------+----------------------
    Mean VIF |      1.74

. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of output

         chi2(1)      =   105.73
         Prob > chi2  =   0.0000

. ovtest

Ramsey RESET test using powers of the fitted values of output
       Ho:  model has no omitted variables
                 F(3, 486) =      6.45
                  Prob > F =      0.0003
```

iii. Raya Azebo group stochastic frontier

```
. reg output labor land oxen seed irregation year

      Source |       SS       df       MS              Number of obs =     158
-------------+------------------------------           F(  6,   151) =   14.62
       Model |  614.697561     6  102.449594           Prob > F      =  0.0000
    Residual |  1057.77629   151  7.00514099           R-squared     =  0.3675
-------------+------------------------------           Adj R-squared =  0.3424
       Total |  1672.47385   157  10.6526997           Root MSE      =  2.6467

------------------------------------------------------------------------------
      output |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       labor |   1.999868    .533762     3.75   0.000     .9452612    3.054474
        land |  -.1702404   .7855606    -0.22   0.829     -1.72235    1.381869
        oxen |  -1.117299   .3721364    -3.00   0.003    -1.852565    -.382032
        seed |  -.4762457   .3404162    -1.40   0.164     -1.14884    .1963483
  irregation |   1.499227   .4993569     3.00   0.003     .5125977    2.485855
        year |   3.130444    .441426     7.09   0.000     2.258275    4.002613
```

```
       _cons |   2.260336   1.832738     1.23   0.219    -1.360785    5.881458
------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF
-------------+----------------------
       labor |      3.69    0.271097
        oxen |      3.15    0.317244
        land |      1.94    0.514317
        seed |      1.70    0.586516
  irregation |      1.10    0.911055
        year |      1.07    0.931627
-------------+----------------------
    Mean VIF |      2.11
. ovtest

Ramsey RESET test using powers of the fitted values of output
       Ho:  model has no omitted variables
                 F(3, 148) =      1.41
                  Prob > F =      0.2410
. hettest
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of output
         chi2(1)      =    38.88
         Prob > chi2  =   0.0000
```

iv. Qolla Temben group stochastic frontier

```
. reg output labor land oxen seed irregation year

      Source |       SS       df       MS              Number of obs =     189
-------------+------------------------------           F(  6,   182) =    7.40
       Model |  82.1454855     6  13.6909142           Prob > F      =  0.0000
    Residual |   336.89165   182  1.85105302           R-squared     =  0.1960
-------------+------------------------------           Adj R-squared =  0.1695
       Total |  419.037135   188  2.22892093           Root MSE      =  1.3605

------------------------------------------------------------------------------
      output |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       labor |  -.1537401   .2251076    -0.68   0.495    -.5978964    .2904162
        land |   1.339788   .4253552     3.15   0.002     .5005265     2.17905
        oxen |   .2714679   .1353669     2.01   0.046     .0043777    .5385582
        seed |   .1565562   .1235741     1.27   0.207    -.0872658    .4003782
  irregation |   .4342923   .2103745     2.06   0.040     .0192058    .8493789
        year |   .1856198   .2069639     0.90   0.371    -.2227374    .5939771
       _cons |   5.227474   .7742629     6.75   0.000     3.699789     6.75516
------------------------------------------------------------------------------
. vif
    Variable |       VIF       1/VIF
-------------+----------------------
       labor |      2.43    0.411530
        oxen |      1.97    0.508798
        land |      1.69    0.592119
        seed |      1.19    0.842128
  irregation |      1.13    0.885402
        year |      1.07    0.933647
-------------+----------------------
```

```
    Mean VIF |      1.58

. ovtest

Ramsey RESET test using powers of the fitted values of output
       Ho:  model has no omitted variables
                 F(3, 179) =      2.50
                  Prob > F =      0.0613
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of output

         chi2(1)      =     6.48
         Prob > chi2  =   0.0109
```

v. Saesie Tsaeda Emba group stochastic frontier

```
. reg output labor land oxen seed irregation year

      Source |       SS       df       MS              Number of obs =     149
-------------+------------------------------           F(  6,   142) =    3.07
       Model | 70.6466593     6  11.7744432           Prob > F      =  0.0074
    Residual |  544.748815   142  3.83625926           R-squared     =  0.1148
-------------+------------------------------           Adj R-squared =  0.0774
       Total |  615.395474   148  4.15807753           Root MSE      =  1.9586

------------------------------------------------------------------------------
      output |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       labor |   1.030262   .3814151     2.70   0.008     .2762761    1.784247
        land |   .1784842   1.006999     0.18   0.860    -1.812163    2.169132
        oxen |  -.2330805   .2634976    -0.88   0.378    -.7539654    .2878045
        seed |  -.0955465    .217452    -0.44   0.661    -.5254079     .334315
  irregation |   .2069371   .3831058     0.54   0.590    -.5503905    .9642648
        year |   .6341431   .3326403     1.91   0.059    -.0234239     1.29171
       _cons |   3.458489   1.306986     2.65   0.009     .8748252    6.042153
------------------------------------------------------------------------------
. vif
    Variable |       VIF       1/VIF
-------------+----------------------
       labor |      3.03    0.329696
        oxen |      2.77    0.360668
        land |      1.52    0.658735
        seed |      1.33    0.750108
  irregation |      1.04    0.957361
        year |      1.04    0.962348
-------------+----------------------
    Mean VIF |      1.79
. ovtest
Ramsey RESET test using powers of the fitted values of output
       Ho:  model has no omitted variables
                 F(3, 139) =      1.30
                  Prob > F =      0.2755
. hettest
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of output
         chi2 (1)      =     5.65
         Prob > chi2 =   0.0174
```