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Technical Efficiency of Smallholder Agriculture in Developing Countries: The Case of Ethiopia

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Abstract: The efficient use of inputs is indispensable in many developing countries, such as Ethiopia. This study assesses the level and determinants of technical efficiency of smallholder farmers using the true fixed effects (TFE) model. The TFE model separates inefficiency from unobserved heterogeneity. Empirical data come from four rounds of panel data (1994–2009) from the Ethiopian rural household survey (ERHS). A one-step maximum likelihood estimator was employed to estimate the Cobb-Douglas stochastic frontier production function and factors influencing technical efficiency. The results indicated that the major variables affecting technical efficiency are policy responsive, albeit to varying degrees: education of the household head, family size, farm size, land fragmentation, land quality, credit use, extension service, off-farm employment, and crop share. The analyses also identify variables amenable to policy changes in the production function: labor, traction power, farm size, seeds, and fertilizer. The mean household-level efficiency for the surveyed farmers is 0.59, indicating that farmers could improve technical efficiency. This implies that smallholder farms in Ethiopia can reduce the input requirement of producing the average output by 41% if their operations become technically efficient. This study recommends that the above policy variables be considered to make Ethiopian smallholder farmers more efficient.

Keywords: technical efficiency; stochastic frontier; Cobb-Douglas production function; true fixed effects model; Ethiopia

JEL Classification: D13; O13; Q12; Q18

1. Introduction

The agricultural sector plays an important role in many developing countries, such as Ethiopia. In Ethiopia, agriculture accounts for 41.1%, 39.6%, 37.5%, 36.3%, 34.9% and 33.3% of gross domestic product (GDP) in 2013/14, 2014/15, 2015/16, 2016/17 and 2017/18, respectively (National Bank of Ethiopia (NBE) 2019), 80% of employment, 70% of raw materials for industry, 85% of food supplies to the country, and 81% of foreign earnings (AfDB 2016). The agricultural sector is considered to be one of the major sectors driving growth. By 2025, 83% of the expected global population of 8.5 billion will reside in developing countries, 140 million of whom will live in Ethiopia. In the same year, Ethiopia aims to become a middle-income country (World Bank 2018). Agriculture in Ethiopia is characterized as being subsistence farming, but plays a crucial role in more than 14 million smallholder farming households and accounts for approximately 95% of agricultural production and 80% of employment (Central Statistics Agency (CSA) Reports). The sector also has one of the lowest productivity levels in the world and involves farming of less than 1.5 hectares per household on average (FAO 2016).

As a consequence, raising agricultural production, productivity, and efficiency remains a fundamental developmental challenge in Ethiopia (Dorosh and Rashid 2013). With an annual population growth of 2.46% (World Bank 2018), Ethiopia must increase its food production to lower prices and ameliorate occasional food shortages. Improving production, productivity, and efficiency in the agricultural sector is essential for meeting these challenges, as is the case in many other developing countries. Thus, studying the technical efficiency levels of smallholder farmers and factors affecting it has important implications for choosing development strategies.

There are limited studies on the technical efficiencies of smallholder farmers and their determinants in Ethiopia. These studies typically employ cross-sectional data, specific geographical areas, and specific crops (Abate et al. 2019; Asefa 2011; Ayele et al. 2019; Dessale 2019; Gela et al. 2019; Geta et al. 2013; Mussa et al. 2012; Tiruneh and Geta 2016; Ulimwengu 2009; Wollie 2018) and use a nonparametric approach (Asefa 2011; Geta et al. 2013; Mussa et al. 2012; Ulimwengu 2009). Moreover, technology and inefficiency are separately estimated using a short panel dataset for the 1994–2004 period (Bachewe 2009). Above all, these studies fail to separate unobserved heterogeneity from inefficiency.

Many studies have focused on separating inefficiency and unobserved heterogeneity in panel data settings under stochastic frontier analysis (Greene 2005a, 2005b; Kumbhakar and Wang 2005; Wang and Ho 2010; Filippini and Greene 2016). Simultaneous estimation of both production technology and the covariates of technical inefficiency is preferred over the traditional two-step procedure (Wang and Schmidt 2002).

By contrast, the present study is relatively comprehensive: it considers more than 60 different crops and 10 animal products, covers the major agricultural regions of the country, simultaneously analyses and estimates the determinants of inefficiency with technology, controls for unobserved heterogeneity, separates unobserved heterogeneity from inefficiency, uses longer panel dataset for the 1994–2009 period, and utilizes large observations (4496).

Enhancing technical efficiency is critical to increasing productivity. Hence, the main objectives of this study were to measure the level and determinants of technical efficiency of smallholder farmers in Ethiopia. This study is one of the first to apply the true fixed effects (TFE) framework. The TFE model plays a vital role in separating inefficiency from unobserved heterogeneity (Greene 2005a, 2005b). As a result, some of the determinant variables become statistically nonsignificant in the TFE model, which reveals that unobserved heterogeneity contributes to this effect. Similarly, the mean household level technical efficiency for the surveyed farmers is 0.59 in the TFE model and that of the time-varying inefficiency effects (TIE) model is 0.36, indicating that the mean household level efficiency in the TFE model is higher than the TIE model specification, indicating that the TFE model differentiates time-varying technical inefficiency from unit specific time invariant unobserved heterogeneity. Moreover, consistent with (Tchale 2009), the TFE model produces higher elasticities and higher average efficiency scores than does the TIE model. The most commonly used inefficiency effects model (Battese and Coelli 1995) that fails to separate inefficiency from unobserved heterogeneity, produced a lower technical efficiency estimate of 0.40 for major crops in Ethiopia (Bachewe 2009). This result is notably lower than the 0.82 estimate for vegetables in Turkey (Bozoğlu and Ceyhan 2007) and 0.83 estimate for oil palm in Indonesia (Alwarritzi et al. 2015), although these results were for specific crops. Larger differences are observed in parameter estimates of inefficiency than in those of technology under the two model specifications. Policymakers should place emphasis on real inefficiency and some of its determinants, as suggested by the TFE model. The results and increased clarity for policy recommendations that follows are promising for future applications of TFE models to agricultural data in developing countries. These results can also serve as a benchmark for farms in developing economies.

2. Methodology

This section provides a brief overview of the panel data stochastic frontier models, methods of technical efficiency analysis, and empirical model specification.

2.1. Brief Overview of the Panel Data Stochastic Frontier Models

The stochastic frontier production function framework independently introduced by (Aigner et al. 1977) and (Meeusen and Broeck 1977) states that such production functions have error terms comprising two parts. The first part accounts for the presence of technical inefficiency in production, i.e., a failure to produce maximum output given inputs and technology. The second part addresses measurement errors in variables, i.e., inherent randomness in output that could arise due to factors such as the weather and the combined effects of unobserved inputs in production.

Generally, in panel data models, inefficiency can be seen as time-invariant (Battese and Coelli 1988; Kumbhakar 1987; Pitt and Lee 1981; Schmidt and Sickles 1984). These first-generation stochastic frontier analysis (SFA) panel models were explicitly developed to account only for the persistent part of inefficiency; i.e., the inefficiency term is assumed to be constant through time but individual-specific. Second-generation stochastic frontier models (Battese and Coelli 1992; Cornwell et al. 1990; Kumbhakar 1990; Lee and Schmidt 1993) also capture time-variant inefficiencies.

The third-generation models take into account unobserved individual effects and time-varying inefficiency (transient inefficiency); i.e., they are three-component models. Here, there are two contrasting perspectives regarding individual effects. The first perspective is that individual effects are treated as long-term (persistent) forms of inefficiency with an additional component to capture time-varying technical inefficiency (Kumbhakar and Heshmati 1995; Kumbhakar and Hjalmarsson 1995). In this case, individual effects are added to persistent inefficiency.

The second perspective is that individual effects are treated as fixed or random, i.e., as something different from inefficiency. Thus, inefficiency in these models is always time-varying and can be either independently and identically distributed (iid) or a function of exogenous variables (Greene 2005a, 2005b; Kumbhakar and Wang 2005; Wang and Ho 2010). In this case, persistent inefficiency is added to individual effects.

The first group of models fails to account for individual effects, which are lumped with persistent inefficiency, while the second group of models fails to capture persistent inefficiency, which is lumped with individual effects.

The fourth generation includes the four-error component models proposed by (Colombi et al. 2011, 2014; Kumbhakar et al. 2014; Tsionas and Kumbhakar 2014). These models seek to overcome the limitations mentioned earlier by accounting for both persistent inefficiency and unobserved individual effects. The general form of the four-error component models is as follows:

$$y_{it} = \beta_0 + f(X_{it}; \beta) + \alpha_i + v_{it} - u_{it} - h_i \tag{1}$$

$$\varepsilon_{it} = \alpha_i + v_{it} - u_{it} - h_i \tag{2}$$

where y_{it} is the log output for individual i at time t; β_0 is a common intercept; X_{it} is the vector of inputs (in logs); β is the associated vector of technology parameters to be estimated; $f(X_{it}; \beta)$ is the production technology; α_i is the individual unobserved effect; v_{it} is a random two-sided noise term (exogenous production shocks); u_{it} is the nonnegative one-sided transient inefficiency; h_i is the nonnegative one-sided persistent inefficiency.

2.2. Technical Efficiency Analysis

Efficiency and productivity have been studied using production, cost, profit, and distance functions. The recent literature shows that production functions commonly have four parts, namely, the deterministic, inefficiency (with two types: persistent and transient), unobserved heterogeneity, and noise parts (Colombi et al. 2011, 2014; Kumbhakar et al. 2014; Tsionas and Kumbhakar 2014).

SFA has two major objectives: estimating underlying production technology and measuring household-specific technical inefficiency (Kumbhakar and Sun 2013). Simultaneous estimation of both production technology and the covariates of technical inefficiency is preferred over the traditional two-step procedure (Wang and Schmidt 2002). When assessing inefficiency, household-specific inefficiency scores are estimated and characterized. The basic concerns of inefficiency analysis include finding inefficiency differences among producers and the exogenous (environmental) factors that can explain these differences. The next concern is how to compute the marginal effects of determinants (environmental variables) on inefficiency. Environmental variables affect the mean and variance of inefficiency as well as the variance of the noise term (Kumbhakar and Sun 2013). Although these variables are not included in the mean or variance of inefficiency, they can affect inefficiency via the variance of the noise component (Kumbhakar and Sun 2013).

The time-varying inefficiency effects (TIE) model developed by (Battese and Coelli 1995) is the most frequently used and popular model among panel data models in inefficiency estimations (Kumbhakar et al. 2014). This model allows for the estimation of exogenous variable influences on inefficiency in the same way as the models of (Greene 2005a, 2005b) do. However, according to the recent development by (Greene 2005a, 2005b), the true random effect (TRE) and TFE models enable the differentiation of time-varying technical inefficiency from unit-specific time-invariant unobserved heterogeneity. These models separate individual effects (fixed or random) from inefficiency, whether inefficiency is iid or a function of exogenous variables (Kumbhakar et al. 2014). Hence, the TRE and TFE models (Greene 2005a, 2005b) and the TIE model specification from (Battese and Coelli 1995) were estimated.

The parametric stochastic frontier method applied in this study is described below. The stochastic production frontier for farmer i in period t is given by Equation (3):

$$Y_{it} = \beta_0 + f(X_{it}; \beta) + \varepsilon_{it} \tag{3}$$

$$\varepsilon_{it} = \alpha_i + v_{it} - u_{it} \tag{4}$$

where Y_{it} is the log of output for individual i at time t; β_0 is a common intercept; X_{it} is the vector of inputs (in logs); β is the associated vector of technology parameters to be estimated; $f(X_{it}; \beta)$ is the production technology; α_i is the individual unobserved effect; v_{it} is a random two-sided noise term (exogenous production shocks); and u_{it} is the nonnegative one-sided inefficiency.

Greene (2005a, 2005b) expands the residual random variation by decomposing the error term into three components Equation (4) and separates individual unobserved effects from inefficiencies. Inefficiency is assumed to take a value between zero and one. Producers who operate below the frontier are inefficient, and those who operate at the frontier are efficient. The inefficiency component of the error term measures the extent of the departure of each producer from the optimal frontier.

Greene (2005a, 2005b) assumes that $[X_{it}, u_{it}, v_{it}]$ are mutually uncorrelated and v_{it} and u_{it} have normal and truncatednormal distributions, respectively. The inefficiency u_{it} is not necessarily time-invariant, instead being allowed to vary through time. In this formulation, α_i contains the cross-unit heterogeneity. The latent time-invariant effects dramatically affect the results. Whether they should represent latent effects of inefficiency or heterogeneity is an important but unresolved question (Greene 2005a). The difference between the TFE and TRE models is the additional assumption that α_i and all other terms in the model are uncorrelated.

Both Greene (2005a, 2005b) and Battese and Coelli (1995) assume that v_{it} are iid and normally distributed with a mean of zero and variance σ_v^2; i.e., v_{it}~N $(0,\sigma_v^2)$ and u_{it} are independently distributed nonnegative truncations of a normally distributed random variable with mean $Z_{it}\delta$ and variance σ_u^2. Here, Z_{it} is a vector of household characteristics, farm characteristics, institutional characteristics, and region-specific variables that affect efficiency, δ is a vector of unknown parameters of the inefficiency equation, and v_{it} and u_{it} are distributed independently of one another and independently of X_{it}.

Greene (2005a, 2005b) and Battese and Coelli (1995) allow u_{it} to be iid or a function of covariates. Given the stochastic production frontier equation, the level of technical efficiency (TE_{it}) of each farm household i in period t is as follows:

$$TE_{it} = \frac{Y_{it}}{(f(X_{it}; \beta)) * \exp(v_{it})} \tag{5}$$

$$\mathrm{TE_{it}} = \exp(-\mathrm{u_{it}}). \tag{6}$$

Because u_{it} is a nonnegative truncation of the normally distributed random variable, TE_{it} can take a maximum value of one and a minimum value of zero. This specification allows efficiency to vary over time. The definition of technical efficiency follows from the notion that if a farm household's actual production level Y_{it} is less than the maximum achievable production level $f(X_{it}, \beta)\exp(v_{it})$, then only idiosyncratic differences exist. Assuming no measurement error, there is some inefficiency on the part of the farmer. The greater the inefficiency, u_{it}, the lower y_{it} is relative to $f(X_{it}, \beta)\exp(v_{it})$. Note that the inefficiency effects u_{it} as well as the symmetric error terms v_{it} may carry the effects of measurement errors in the dependent variables, just as in any other econometric model.

Since u_{it} is assumed to be time variant, panel data that have within-group variation may allow an analysis of both inefficiency and heterogeneity. However, time persistent inefficiency is overlooked under this specification, so this extension will only partially solve the problem i.e., separating inefficiency and heterogeneity. This specification separates the 'noise' from the time-variant inefficiency effects, but is unable to separate time-invariant unobserved heterogeneity from persistent inefficiency.

Technical inefficiency is assumed to be a function of exogenous variables, Z_{it}. A set of parameter values, δ, is estimated simultaneously with the production function parameters. The inefficiency equation is given by Equation (7):

$$\mathrm{u_{it}} = \mathrm{Z_{it}}\delta + \mathrm{w_{it}} \tag{7}$$

where w_{it} is a random variable that is assumed to be distributed with a mean of zero and variance σ_w^2. u_{it} is defined by the truncation of the normal distribution, with the point of truncation given by $-Z_{it}\delta$ because $u_{it} = Z_{it}\delta + w_{it} \geq 0$, where $w_{it} \geq -Z_{it}\delta$, such that w_{it} is truncated from below. Hence, u_{it} is assumed to be a positive and truncated normally distributed variable with a constant mean and σ_u^2 variance. Thus, $u_{it} \sim N\left(\mu, \sigma_u^2\right)$.

2.3. Empirical Model

In this paper, the SFA approach is employed to estimate technology and evaluate technical efficiency and its determinants. The Cobb-Douglas functional form is used to specify the stochastic production frontier despite its well-known limitations compared to other flexible functional forms, such as the translog and quadratic forms. First, these flexible functional forms are known to be vulnerable to multicollinearity problems (Lyu et al. 1984; Pavelescu 2011). Second, the paper rests on the determinants of efficiency and not on analysis of the general structure of production technology. Third, the production function has many inputs and environmental variables that cause convergence problems. Fourth, the Cobb-Douglas production function gives better estimates when some of the basic assumptions are violated and fits a range of datasets (Miller 2008). It has been argued that the Cobb-Douglas production function provides an acceptable representation of production technology (Taylor et al. 1986). The logarithmic form of this Cobb-Douglas specification is as follows:

$$\mathrm{lnY_{it}} = \beta_0 + \alpha_i + \beta_j \mathrm{lnX_{it}} + \mathrm{v_{it}} + \mathrm{u_{it}} \tag{8}$$

where $t \in (1, 6, 11, 16)$ is the period for which data are available in 1994, 1999, 2004, and 2009, $i \in (1, 2, 3, \ldots, 1195)$ represents farmer i, β_0 is the constant term, α_i is the unobserved heterogeneity, β_j is a vector of the coefficients of the production function to be estimated, X_{it} is a vector of inputs of the farmer, v_{it} are the idiosyncratic error terms, and u_{it} are inefficiencies. The variable $\ln Y_{it}$ is the logarithm of the real value of the output of household i in period t.

The inefficiency equation (u_{it}) is explained by a vector of the covariate Z_{it}. Taking into account environmental variables (Z_{it}) such as household characteristics, farm characteristics, institutional characteristics, region specifics, and others, the inefficiency equation (u_{it}) is given by Equation (7):

$$\mathrm{u_{it}} = \delta_0 + \delta_i \mathrm{Z_{it}} + \mathrm{w_{it}} \tag{9}$$

where δ_i are the coefficients of the environmental variables to be estimated; δ_0 is the constant term; w_{it} is the noise term of the inefficiency equation.

To estimate the Cobb-Douglas production function, farm size, labor, traction power, fertilizer, seed, asset, and precipitation variables are converted to logs so that the first-order parameters can be interpreted as elasticities. Other categorical variables that can shift the frontier are also controlled. A maximum likelihood estimator, as implemented in the STATA 13® module sfpanel (StataCorp 2013), is used to estimate Equations (8) and (9) simultaneously. Cobb-Douglas technology, time-varying technical inefficiency and truncated normally distributed technical inefficiency models are estimated.

3. Data

This study used the Ethiopia Rural Household Survey (ERHS) dataset, which includes a panel of 1195 households and 4194 observations over the period from 1994 to 2009 consisting of four collections every five years. This dataset was collected from four major regions of Ethiopia, namely, Amhara, Oromia, the Southern Nation Nationalities and Peoples' (SNNP), and Tigray. These regions are four of the nine administrative regions in the country and include approximately 86% of the Ethiopian population. Further details on the data can be found in Appendix A .

4. Results and Discussion

This section provides descriptive statistics of the important variables in the models, estimates of the level and determinants of technical efficiency of smallholders using simultaneous stochastic frontier estimation techniques.

4.1. Descriptive Statistics of Variables

Farmers produce more than 60 crops and 10 animal products. The analysis considers all the values of these products. Some of the major plant products are *teff*, maize, wheat, barley, sorghum, coffee, chat, *enset*, legumes, and vegetables. Some of the major animal products are meat (including that from chickens), hides, skins, butter, cheese, milk, and eggs. Sole cropping is the most common agricultural practice in Ethiopia, followed by mixed cropping.

Tables A1 and A2 provide descriptive statistics of the variables in the model during the study period (1994–2009). Farmers' output consists of crops and animal products valued at market price. The main inputs include land, labor, traction power, fertilizer, seeds, assets, precipitation, soil fertility, and hoes. All monetary value measures are expressed using the producer price index, taking the 1994 prices as a base. However, obtaining input prices in developing countries is very difficult due to market failures.

Land is the basic asset of farmers in Ethiopia. The mean farm size is approximately 1.5 hectares per household. The soil fertility of the plots is medium, on average, and approximately 47% of the farms have 'good' soil fertility. Another indicator of soil fertility is the land quality index,[1] which takes soil fertility and slope into account. On average, farms have a land quality index of 6.49, with a minimum of 1 and a maximum of 9. The average number of plots per household is 5. In general, farmers have fragmented land.

After land, livestock is the most important asset for rural households in Ethiopia, and it is used as a source of draft power, food, income, and energy. The primary purpose of raising cattle in most parts of the country is to produce oxen for plowing and threshing. Moreover, livestock is an index of

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1 The average land quality index is calculated as a product of the natural conditions of two indices that assign a value of 3 if the slope is flat and a value of 3 if the land is fertile in terms of mineral content. A high index value indicates better soil fertility. The average land quality is best in terms of slope and mineral content when given a value of 9, with a value of 1 indicating the lowest land quality evaluated at the household level.

wealth and prestige in Ethiopia's rural communities. Approximately 86% of the sample households rear livestock, which consist of cattle, small ruminants, pack animals, and poultry, among others.

Labor refers to the total number of members in a household in adult equivalent units. In general, the larger the number of household members, the larger the labor force available for production purposes, given a lower dependency ratio.[2] The average age of the household head is approximately 50 years. The average household size in the sample is approximately 6.7 persons, and the labor force contribution to the production process for the study period is approximately 4 adult equivalent units. Approximately 20% of the sample households are headed by females.

Fertilizer application for production is measured by households' fertilizer expenses. Fewer than half of the sample households (47%) used fertilizer, and the average amount of money spent on fertilizer was 340 Ethiopian birr for those who used fertilizer. This fertilizer application rate is far below the recommended rate. Approximately 30%–40% of Ethiopian smallholder farmers use fertilizer, which they apply at the rate of 37–40 kilograms per hectare, and this rate is significantly below recommended rates (Spielman et al. 2012). In Ethiopia, fertilizer expenses were subsidized by the federal government until 1991. However, after 1991, fertilizer and seed prices were subsidized only by regional governments, and these subsidies were eliminated in 2007.

Seeds are a basic input for improving crop production and productivity. More specifically, improved seeds can increase the yield potential of the crop and thereby increase efficiencies. Improved seeds, next to fertilizer, are the most widely used modern input in Ethiopian agriculture. However, they covered less than4% of the total cultivated land in the survey period (1994–2009). The use of improved seeds is more common in the production of cereals than for any other crop. Nonetheless, less than 5% of the area with cereals was planted using improved seeds. Among cereals, maize, wheat, *teff*, and sorghum are the most important crops for which improved seeds are used in Ethiopia (CSA Reports 2009–2014). However, improved seed use is nonexistent in rural areas (FAO 2006). For this paper, local and improved seeds are added together as 'seeds'.

The number of hoes used for land preparation is also accounted for. Hoes are used for land preparation and weeding. Hoe farming mainly takes place in the enset-growing region, where oxen farming is minimal. Approximately 64% of the sample households use hoes for land preparation, and these households each have two hoes on average.

Precipitation is one of the most important factors for production on which Ethiopian agriculture relies. More than 96% of Ethiopian agriculture depends on rainfall (CSA Reports 2009–2014). The frequent drought that affects the country is caused by low and highly unpredictable rainfall.

Asset/wealth is used as an indicator of producers' risk behavior in agriculture. Farmers' risk behavior determines input allocation decisions and thereby limits output (Berbel 1990; Guiso and Paiella 2008; Kumbhakar 2002; Salimonu and Falusi 2007). Farmers in developing countries are generally skeptical of using their scarce inputs for activities with high risk. This has led to the current practice being of low risk and low return (Collier and Gunning 1999).

Education plays an important role in enhancing the utilization of farm inputs and in the willingness to adopt new technologies. Human capital formation can improve agricultural production efficiency (Solís et al. 2009). However, only 39% of the household heads have some level of schooling that enables them to read and write.

Credit plays a crucial role in rural communities, and inadequate access to credit may affect farmers' decisions. Agricultural credit enhances productivity and promotes a higher standard of living by filling the financial gaps of smallholder farmers. Credit provided in a timely manner for production purposes benefits smallholder farmers (Tenaye 2009). Currently, credit provision in Ethiopia lacks

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[2] The number of dependents (aged 0–9 and over the age of 65) relative to the number of active members in a household (aged 10–65).

diversification that might minimize risk. In this study, approximately 52% of the sample households received credit to purchase farm inputs such as seeds and fertilizer.

In this study, the observed heterogeneity in smallholder farmers in Ethiopia was controlled using input covariates in the technology and environmental variables of inefficiency models. Nevertheless, other observed and unobserved factors beyond farmers' control may affect their efficiency. Hence, an econometric method is required to control for both observed and unobserved heterogeneity. The Greene TFE and TRE models were chosen to separate time-varying technical inefficiency from unit-specific time-invariant unobserved heterogeneity (Greene 2005a, 2005b). The Hausman test was conducted to determine whether the TFE or TRE model is a more appropriate model. The TRE model is more efficient, but its parameters will be biased if the Hausman test rejects the null hypothesis of no correlation between unobserved heterogeneity and the model error term. The test suggests that the TFE model is more appropriate than the TRE model. Therefore, the TFE model is used for final estimation.

In addition, tests are conducted to choose a more parsimonious specification. Restrictions for constant returns to scale, no unobserved heterogeneity, no observed heterogeneity, the assumption of constant inefficiency over time, and the assumption of a no truncated normal distribution for technical inefficiency (see Table 1) are rejected at the 1% level of significance. Therefore, unconstrained technology and a time-varying and truncated normal distribution for technical inefficiency were estimated.

Table 1. Properties of the Ethiopian farms' household technology.

Restriction	Parametric Restriction	Wald Test Statistic	*p*-Value
Constant return-to-scale technology	$H_0: \sum_{k=1}^{K} \beta_i = 0$	0.098	0.000
No unobserved heterogeneity	$H_0: \mathrm{Var}(u_{it}) = 0$	279.85	0.000
No observed heterogeneity	$H_0: \delta_1 = \delta_2 = \ldots = \delta_{16} = 0$	4.6×10^{11}	0.000
Constant inefficiency	H_0: eta $(\eta) = 0$	51.66	0.000
No truncated normal distribution for technical inefficiency	$H_0:$ mu $(\mu) = 0$	25.95	0.000

Source: Author's calculation.

Furthermore, robustness checks are conducted under alternative specifications. The robustness checks show how 'core' regression coefficient estimates behave when the regression specification is changed in some way, usually by adding or removing regressors (Lu and White 2014). These alternative specifications are presented in Tables A3 and A4.

The TFE model that controls unobserved heterogeneity and separates it from inefficiency is estimated and compared with the TIE model. The production technology, inefficiency scores and determinants of inefficiency are estimated for smallholder farmers in Ethiopia. This result may serve as a benchmark for farms in developing economies. Major inputs and environmental variables are controlled for in the SFA. However, there are other observed and unobserved factors that are beyond farmers' control that may affect their efficiency. Hence, TFE and TRE models play a vital role in separating inefficiency from unobserved heterogeneity (Greene 2005a, 2005b). When the Greene models that separate inefficiency from unobserved heterogeneity are used, some of the determinant variables become statistically nonsignificant in the TFE model, which reveals that unobserved heterogeneity contributes to this effect. Moreover, the TFE model produces higher elasticities and higher average efficiency scores than does the TIE model. Larger differences are observed in parameter estimates of inefficiency than in those of technology under the two model specifications. As a result, policymakers should place emphasis on real inefficiency and some of its determinants, as suggested by the TFE model.

As noted, the panel SFA, which accounts for both observed and unobserved heterogeneity, enables consistent estimation of both technology and efficiency parameters (Kumbhakar et al. 2014). The SFA model is estimated using single-stage maximum likelihood estimation based on the TFE model because of its ability to separate inefficiency from observed and unobserved heterogeneity (Greene 2004, 2005a, 2005b). The inefficiency effects model (Battese and Coelli 1995) that fails to separate inefficiency from unobserved heterogeneity is also estimated for comparison purposes. In this case, different covariates are statistically significant.

4.2. Simultaneous Stochastic Frontier Estimates of Technology and Technical Efficiency

The simultaneously estimated parameters of the unrestricted model, the truncated normal distribution for technical inefficiency and its determinants are reported in Table 2. The results show that both TFE and TIE models produce the expected signs and somewhat comparable estimates of technology parameters. The first-order parameters of inputs have the expected signs in the two models. All input variables including production function shifters are significant at the 1% level of significance under the TFE model. Labor, farm size, traction power, precipitation, fertilizer use, seeds, assets, soil fertility, hoe use, and agroecological zones (AEZs) have stronger and statistically significant effects on farm output (elasticity and production function shifter) in the TFE model compared with the TIE model. The TIE model analysis yields somewhat different results. Here, lower and significant elasticities are found for the abovementioned inputs and outputted augmented variables. The mean household-level efficiency score in the TFE model is higher (58.6%) than that in the TIE model (36.2%), indicating that the TFE model differentiates time-varying technical inefficiency from unit-specific time-invariant unobserved heterogeneity, in contrast to the TIE model.

In addition, the sources of inefficiency in both models were identified. Here, quite different results are obtained from the two models. Age and education of the household head, family size, farm size, land quality, land fragmentation, credit use, access to extension service, participation in off-farm activities, crop share to total farm income, and AEZ statistically significantly affect farm household technical efficiency in the TFE model.

As shown in Table 2, higher and statistically significant elasticities are found for precipitation (0.51), labor (0.30), farm size (0.12), assets (0.08), traction power (0.04), seeds (0.04), and fertilizer (0.01) in the TFE model than in the TIE model. Farms implementing hoes and with higher soil fertility produce more than their counterparts. The trend variable shows that production increases over time. The traditional TIE model analysis yields smaller statistically significant elasticities for precipitation (0.13), labor (0.11), farm size (0.42), assets (0.03), traction power (0.05), seeds (0.03), and fertilizer (0.02). Similar estimates of elasticities were reported for Chinese agriculture (Liu and Zhuang 2000).

Categorical variables, such as soil fertility, AEZ and hoe use, which can shift the frontier, are also taken into account. These categorical variables significantly affect farm output. The five major AEZs are controlled for to account for environmental differences and are statistically significant at the 1% level, and all other AEZs are at higher production levels than the northern agroecological zone. Note that gender is statistically significant and hence affects farm household efficiency and that age, farm size, and land qualities are not significant in the TIE model.

Table 2. Parameter estimates of Cobb-Douglas stochastic frontier analysis under true fixed and time-varying inefficiency effects models.

True Fixed Effect (TFE) Model: Controls for Observed and Unobserved Heterogeneity				Time-Varying Inefficiency Effects (TIE) Model		
Variables	**Estimate**	**SE**	**Z-Test**	**Estimate**	**SE**	**Z-Test**
lnx1 (Farm size (hectares))	0.120 ***	3.92×10^{-5}	3052.32	0.418 ***	0.029	14.38
lnx2 (Labor (adult equi. units))	0.304 ***	4.59×10^{-5}	6615.33	0.107 ***	0.024	4.31
lnx3 (Oxen (number))	0.041 ***	1.07×10^{-5}	3801.45	0.045 ***	0.004	11.26
lnx5 (Precipitation (mm))	0.508 ***	4.47×10^{-5}	1.1×10^{4}	0.138 ***	0.046	2.97
lnx6 (Seeds (value))	0.042 ***	2.11×10^{-5}	1994.71	0.034 ***	0.006	6.02
lnx7 (Fertilizer (value))	0.006 ***	86.7×10^{-6}	667.92	0.017 ***	0.002	7.66
x8 (Hoe dummy)	0.076 ***	9.81×10^{-5}	775.33	0.155 ***	0.031	4.97
lnx9 (Asset (value))	0.078 ***	9.89×10^{-6}	7889.59	0.031 ***	0.006	4.82
x10 (Soil fertility dummy)	0.023 ***	13.03×10^{-5}	179.22	0.220 ***	0.038	5.79
x11 (AEZ)	Northern highlands agroecological zone					
Enset, hoe	4.530 ***	13.03×10^{-5}	3.0×10^{4}	4.489	5.619	0.80
Hararghe, oxen	2.844 ***	17.87×10^{-5}	1.6×10^{4}	0.923 ***	0.137	6.73
Arussi/Bale	2.645 ***	17.41×10^{-5}	1.5×10^{4}	0.708 ***	0.133	5.32
Central highlands	2.396 ***	16.79×10^{-5}	1.4×10^{4}	0.269 ***	0.079	3.41
T (Time (years))	0.228 ***	4.69×10^{-5}	4856.28	0.021	0.023	0.91
Exogenous inefficiency determinants:						
δ1 (Gender (male = 1))	0.266	0.783	0.34	−0.278 ***	0.071	−3.92
δ2 (Age (years))	−0.235 *	0.135	−1.79	0.002	0.011	0.22
δ3 (Age2)	0.002 *	0.001	1.69	−0.000	0.000	−0.60
δ 4 (Education dummy)	−1.363 **	0.719	−1.89	−0.239 ***	0.060	−3.99
δ5 (Family size (number))	0.270 **	0.109	2.48	−0.021 **	0.010	−2.19
δ6 (Farm size (hectares))	−0.754 ***	0.146	−5.16	−0.010	0.013	−0.77
δ7 (Land quality index)	−0.275 **	0.138	−1.99	0.003	0.017	0.16
δ8 (Land fragmentation (number))	1.088 ***	0.265	4.10	0.194 ***	0.021	9.10
δ9 (Credit dummy)	1.255 **	0.627	2.00	0.282 ***	0.054	5.21
δ10 (Extension dummy)	−0.529 *	0.306	−1.73	−0.059 **	0.024	−2.48
δ11 (Market distance (minutes))	0.008	0.009	0.91	−0.005 ***	0.001	−4.96
δ12 (Off-farm income dummy)	1.224 *	0.635	1.93	0.165 ***	0.055	2.98
δ13 (Crop share)	−5.091 ***	1.935	−2.63	−0.512 ***	0.182	−2.81
δ14 (AEZ)	Northern highlands					
Enset, hoe	12.567 ***	2.038	6.16	5.815	5.630	1.03
Hararghe, oxen	9.073 ***	2.073	4.38	1.545 ***	0.387	4.00
Arussi/Bale	14.330 ***	2.656	5.40	2.245 ***	0.346	6.49
Central highlands	7.787 ***	2.388	3.26	0.726 **	0.353	2.06
T (years)	0.071	0.656	0.11	0.162 **	0.074	2.20
δ16 (AEZs-T interaction)	−0.514 **	0.210	−2.45	−0.148 ***	0.029	−5.03
Constant	−11.664 ***	3.558	−3.28	0.145	0.512	0.28
Sigma(u) constant	2.760 ***	0.157	17.57	−0.007	0.055	−0.12
Sigma(v) constant	−30.134 *	18.240	−1.65	−0.946 ***	0.077	−12.21
Sigma(u): δ_u^2	3.975 ***	0.312	12.73	0.997 ***	0.027	36.42
Sigma(v): δ_v^2	2.86×10^{-7}	2.61×10^{-6}	0.11	0.623 ***	0.024	25.82
Lambda: $\lambda = \frac{\delta_u^2}{\delta_v^2}$	1.39×10^{7} ***	0.312	4.5×10^{7}	1.599 ***	0.044	36.75
Gamma: $\gamma = \frac{\delta_u^2}{\delta_u^2 + \delta_v^2}$	0.999	-	-	0.615	-	-
Wald chi2 (14) p-value	3.14×10^{10}	-	-	868.99	-	-
Prob. chi2	0.000	-	-	0.000	-	-
Log likelihood function	−3427.15	-	-	−6019.58	-	-
Number of households	**1195**		**Observations**	**4194**	**-**	**-**

Source: Author's calculation. SE = standard error, *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Values are expressed in 1994 prices by using the producer price index in birr. Birr is the Ethiopian currency: 1USD = 5.22 birr in 1994, 1USD = 7.81 birr in 1999, 1USD = 8.34 birr in 2004 and 1USD = 11.53 birr in 2009 when the data were collected. Source: http://www.gocurrency.com/v2/historic-exchange-rates.php-.

4.3. Determinants of the Technical Efficiency of Smallholder Farmers

Time-varying technical efficiency scores for each farm household are obtained from the composite error term using the conditional expectation predictor developed by (Jondrow et al. 1982). The time-variant inefficiency model was estimated because the time-variant inefficiency component, eta (η), was negative and statistically significant. This implies that there is statistical evidence for a decline in technical efficiency over time. Therefore, there are valid statistical grounds to conclude that inefficiency is time varying. Hence, the more general time-varying inefficiency specification models are estimated.

The hypothesis of an unobserved individual effect was also tested using the Breusch and Pagan Lagrangian multiplier test for random effects, which confirmed that there are unobserved individual effects. Therefore, it is realistic to employ a model that considers unobserved heterogeneity and time-varying inefficiency, such as Greene's models (TRE and TFE models).

Production technology and inefficiency were estimated simultaneously. The technology and inefficiency parameters are statistically significant with the expected signs. As shown in Table 2, the parameter lambda (λ) indicates the share of technical inefficiency in the total error variance, and the parameter gamma (γ), which is similarly reparameterized, indicates the share of total variance accounted for by inefficiency. They are very large numbers in the case of the TFE model, measuring 1.39e + 8% and 99.9, respectively. These values are approximately 1.60% and 61.5% in the case of the traditional TIE model. The higher values for the former model suggest the appropriateness of the frontier approach compared with the least squares approach.

The average technical efficiency score is 0.586 with a standard deviation of 0.339 in the TFE model specification, whereas it is 0.362 with a standard deviation of 0.295 in the case of the traditional TIE model specification. This result indicates that an average farmer produces 58.6% (36.2%) of the value of output produced by the most efficient farmer using the same technology and inputs under the TFE (TIE) model. The mean household-level efficiency for the surveyed farmers in the TFE model is higher than that found in the traditional TIE model specification, indicating that the TFE model differentiates time-varying technical inefficiency from unit-specific time-invariant unobserved heterogeneity. The range of the efficiency score is much wider in the TFE model (0.0001306–0.9999986) than in the traditional TIE model (0.0000832–0.8928707). Regardless, farmers in Ethiopia can improve their technical efficiency by fully utilizing their existing inputs and technology. They can reduce the input requirements for producing the average output by 41.4% (64.2%) in the TFE (TIE) model if their operation becomes technically efficient. The scale coefficient is 1.10 (0.79) in the TFE (TIE) model, which indicates that farmers are operating under increasing returns to scale in the case of the TFE model. In general, managerial skills, resource constraints, fragmentation of landholding, and infrastructure significantly determine efficiency. Asefa reports similar estimates of technical efficiency scores for crop-producing smallholder farmers in Tigray, Ethiopia, using a Cobb-Douglas production function (Asefa 2011). However, a few studies report lower technical efficiency estimate scores (0.40) (Bachewe 2009; Geta et al. 2013) while others report higher scores (0.75) (Abate et al. 2019; Dessale 2019) using cross-sectional data and the Cobb-Douglas production function for specific crops (wheat and red pepper) in Ethiopia. The difference in average efficiency scores can be explained by the use of cross-sectional data, smaller sample sizes, few crops, and different specifications and estimation methods. Estimation of technical efficiency is sensitive to the assumptions regarding the inefficiency distribution and estimation method used (Kumbhakar et al. 2014; Wang and Schmidt 2002).

Assessing determinants of agricultural production efficiency is more important than merely presenting a set of efficiency indices for designing agricultural policy to improve smallholders' agricultural productivity and efficiency and hence reduce resource waste and improve farmers' livelihoods. The parameter estimates of the inefficiency effects obtained with the stochastic production frontier model employed to identify the determinants of technical inefficiency and measure technology are simultaneously estimated using the maximum likelihood estimator. Table 2 presents the determinants of technical inefficiency in Ethiopian agriculture. These findings can be divided into three categories:

1. Significant factors that can be influenced by (agricultural) policy: education of the household head, family size, farm size, land fertility, fragmentation, credit use, extension service, off-farm income participation, and crop share.
2. Significant factors that cannot be influenced by (agricultural) policy or are difficult to influence: AEZ and age of the household head.
3. Nonsignificant factors: gender and market access.

The positive or negative signs of the estimates for these z-variables indicate that there is an increase or a decrease in technical inefficiency, respectively. A negative estimate indicates a positive effect on technical efficiency.

Household characteristics significantly affect technical efficiency. More specifically, the age of the household head has a negative and significant coefficient for technical inefficiency, implying that older farmers are more efficient than younger farmers. This is because older farmers have more experience and more contacts with extension agents. Moreover, age squared has a positive and significant effect on technical inefficiency, which implies that much older farmers are less willing to adopt new technologies and are more risk averse. The finding that age significantly positively affects technical efficiency is also consistent with the findings of other studies in the agriculture literature (Abate et al. 2019; Asefa 2011; Ayele et al. 2019; Dessale 2019; Tian et al. 2015). Farmer age might also have a negative impact on technical efficiency. Here, it appears that much older farmers are less willing to adopt new practices and modern inputs than young farmers are (Battese and Coelli 1995; Bozoğlu and Ceyhan 2007).

Human labor (quality and quantity) determines technical efficiency. The labor quality indicator education is a dummy variable that is equal to 1 if the household head can read and write and 0 otherwise. As expected, education has a negative and significant effect on technical inefficiency, which implies that farmers who can read and write have more technical efficiency than their counterparts. The ability to read and write makes information accessible, which in turn fosters improved understanding. Hence, educated farmers tend to be more responsive to new technologies, which improve their technical efficiency. Education also enhances farmers' managerial skills, including the efficient use of agricultural inputs. The finding that education significantly and positively affects technical efficiency is also in line with earlier findings reported in the literature (Abate et al. 2019; Alwarritzi et al. 2015; Ayele et al. 2019; Dessale 2019; Seyoum 2013; Tian et al. 2015).

Family size has a positive and significant coefficient with technical inefficiency. This can be explained by the fact that rural areas have a more flexible supply of in-house labor. This also relates to the dependency ratio. This finding is consistent with those others in the literature (Abate et al. 2019; Mussa et al. 2012; Tchale 2009) which show that larger families are more technically inefficient. However, Asefa (2011) reports the opposite result. This study shows that excess labor could be used for off-farm activities (for example, service and industry) without negatively affecting the agricultural sector (Lien et al. 2010).

Farm size has a negative and significant effect on technical inefficiency. This indicates that large farms are more technically efficient than small farms. The estimated coefficient for cultivated areas confirms that farmers' efficiency improves with an increase in farm size. Considering the small average farm size of Ethiopian farms (1.5 ha), one would expect that increasing farm size would improve technical efficiency through reduced management costs and increase flexibility in the use of other inputs. This finding is supported by some studies (Bozoğlu and Ceyhan 2007; Geta et al. 2013; Tipi et al. 2009), the authors of which conclude there is a positive relationship between farm size and technical efficiency. However, others argue the opposite (Huang and Bagi 1984; Squires and Tabor 1991).

An average land quality index is used to control for soil fertility by taking the slope and mineral quality of the cultivated land into account. Not only the quantity of land but also its quality is crucial to increasing productivity and efficiency. The quality of land is negatively associated with technical inefficiency. Thus, farmers operating on more fertile plots perform significantly better than their counterparts, thereby strengthening the argument that improvement in soil fertility is a decisive element in increasing efficiency and productivity. This finding is consistent with that of Zhang et al. (2016).

Land fragmentation[3] as one of the important determinants of inefficiency is one of the most significant findings of the study. More specifically, fragmentation of farmland has a positive and significant effect on technical inefficiency, as expected. Land fragmentation increases boundary areas that are not planted and hence decreases the operated farm area. Moreover, one would expect land fragmentation to increase farm management costs because of the increased number of plots. It also lowers soil and water conservation activities since it requires collaboration among farmers. Moreover, there is low productivity around boundaries because they lower the input application rate, serve as routes, and act as cover for nearby grazing animals. Furthermore, fragmented land causes time loss in travel and inconvenience in agricultural management. Increasing farm size from the current size minimizes land management and area wastage at boundaries and hence improves technical efficiency. Farmers can collectively use modern inputs (for example, tractors and combine harvesters) in their common areas to avoid boundaries and increase farm size, thereby increasing the efficient use of resources. This finding is consistent with those of Ayele et al. (2019); Manjunatha et al. (2013); Bachewe (2009); Tipi et al. (2009), who conclude that there is a negative correlation between land fragmentation and technical efficiency. However, land fragmentation also has positive effects by reducing risks through spatial diversification of farming activities and improved flexibility of the optimal timing of farm operations (Abate et al. 2019).

Credit use is another dummy variable affecting technical efficiency. It equals 1 if farmers use credit and 0 otherwise. Unexpectedly, credit use has a positive and significant effect on technical inefficiency in the study area, which indicates that borrower farmers are more inefficient than nonborrower farms. The main reason for the negative relationship between credit use and efficiency is that only approximately 34% of the farmers with credit use their credit for production purposes. The remaining 66% of farmers with credit divert their credit from production to consumption. However, a mean comparison t-test confirmed that a statistically significant difference in efficiency score between farmers who used credit for production (0.60) and who used for consumption (0.57). Tenaye (2009) argues that farm credit negatively affects production because it is provided in an untimely manner and in lower amounts than needed and diverted from production to consumption. (Bachewe 2012) argues that some unobservable factors associated with acquiring credit, such as processing costs, insufficient credit, a lack of service use by those with sufficient funds and a targeting problem, are the reasons for this unexpected outcome. This finding is in line with results reported by Abate et al. (2019) and Mussa et al. (2012). However, others argue that credit positively affects technical efficiency (Asefa 2011; Bozoğlu and Ceyhan 2007; Dessale 2019). In general, one would expect credit to enhance the ability of farmers to adopt new technologies and improve efficiency.

Extension service is a dummy variable that equals 1 if the farmer received extension service from the development agent in the last cropping season and 0 otherwise. As expected, extension service has a negative and significant effect on technical inefficiency, implying that farmers who receive extension service from the development agent have lower inefficiency. The development agent provides agricultural extension services, including training and practice in agronomy, crop protection, input use (e.g., seeds and fertilizer), soil conservation, and other activities. All these factors are expected to have a positive impact on technical efficiency. Extension service positively influences technical efficiency, according to earlier findings reported in the literature (Alwarritzi et al. 2015; Ayele et al. 2019; Solís et al. 2009; Tipi et al. 2009).

[3] Land fragmentation is calculated as the product of farm size and the number of plots. It is reasonable to include this interaction term in inefficiency equations to see the effect of land fragmentation on efficiency. First, for a given area of cultivated land, the larger the number of plots is, the greater the distance the farmer is likely to have to travel to tend the plots, thus increasing technical inefficiency. Second, plots that are located sufficiently far apart minimize production loss due to risks related to weather, pests, diseases and low soil fertility. The data reveal an increase in the number of plots farmed over the years, from 4.3 in 1994 to 5.5 in 2009.

About 42% of the sample households participated in off-farm activities and generated about 6.8% of their annual income. Participation in off-farm employment is the other dummy variable, which equals 1 if the farmers participate in off-farm activities and 0 otherwise. Off-farm employment participation can have both positive and negative impacts on efficiency. It may have a positive effect if off-farm activity is scheduled in the offseason and the income generated is used to purchase production inputs. On the other hand, if it is scheduled in season and the income is used for nonproduction activity, it may have a negative effect on technical efficiency. In this study, off-farm income participation has positive and significant effects on technical inefficiency, indicating that off-farm income participation comes at the expense of farming activities. This finding is consistent with the results reported by several authors in the literature, such as Mussa et al. (2012); Tipi et al. (2009); Bozoğlu and Ceyhan (2007).

Crop share[4] has a negative and significant effect on technical inefficiency. This implies that mixed farming is more efficient. A plausible reason for this result is that mixed farms have increased flexibility in their time use and better access to oxen, which enables farming of larger areas and better tillage. Crop residue is an input for animal production; likewise, animal production is a source of draft power and organic manure for crop production. If these factors compete, then they compete slightly for labor and land, which are managed systematically in Ethiopian farming communities. This confirms the finding (Alwarritzi et al. 2015; Coelli and Fleming 2004) that farm diversification activities seem to increase efficiency because the farmers might have the opportunity to choose other farming activities that complement the given input of each other resource. However, Baležentis et al. (2014) argue that specialization increases efficiency.

Technical efficiency varies across AEZs, and Arussi-Bale, enset farming, Hararghe, and the central highlands have higher efficiency than the northern AEZ. However, the time variable is not statistically significant, implying that there is no significant time trend for technical efficiency. The interaction of AEZ and time is statistically significant, implying that there are environment and time interaction effects that increase efficiency. The negative time trend of inefficiency interacting with AEZs could be partly explained by inefficiency variation across AEZs and partly by an increase in land quality, which is measured by the land quality index.

Finally, estimates of the marginal effects of age, farm size, land quality, and crop share are found to be 0.24%, 0.75%, 0.28%, and 5.10%, respectively, with a positive effect on technical efficiency. Farms with educated heads of household and that use the extension service have higher technical efficiency scores than their counterparts. Environment-time interaction also increases technical efficiency. Age squared, family size, and land fragmentation reduce efficiency by 0.002%, 0.27%, and 1.08%, respectively, when increased by 1 unit. Farms that use credit and participate in off-farm activities have lower technical efficiency scores than their counterparts (Table 2).

4.4. Mean Difference in Technical Efficiency across Regions and AEZs of Smallholder Farmers

As shown in Table 3, technical efficiency has been somewhat constant over time, except when it was slightly lower in 2004. The yearly average technical efficiency was 54.3%, 60.4%, 58.7%, and 60.7% in 1994, 1999, 2004, and 2009, respectively, in the case of the TFE model. These figures indicate that households utilized farming techniques similar to those used by the best performers in the agricultural sector over these periods, despite significant room for improvement. Table 4 also presents regional efficiency scores, showing that the Oromia, Tigray, and Amhara region scores are at or above the national average, whereas the SNNPR efficiency scores were lower than the national average. This result can be explained by the fact that regional variation is controlled by agroecological variables, soil fertility, and rainfall amount.

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[4] Crop share is the proportion of income from crop production relative to income from both crop and animal production.

Table 3. Technical efficiency of Ethiopian farm households over years, across regions, and across Agroecological zones (AEZs) in the True Fixed Effect (TFE) model.

Year	Technical Efficiency	Region	Technical Efficiency	AEZ	Technical Efficiency
1994	0.543	Tigray	0.624	Northern highlands	0.651
1999	0.604	Amhara	0.643	Enset (hoe)	0.527
2004	0.587	Oromia	0.582	Hararghe (oxen)	0.571
2009	0.607	SNNPR	0.527	Arussi-Bale	0.561
-	-	-	-	Central highlands	0.632
Average	0.586	-	0.586		0.586

Source: Author's calculation.

Table 4. Technical efficiency of Ethiopian farm households over years, across regions and across AEZs in the Time-varying Inefficiency Effects (TIE) model.

Year	Technical Efficiency	Region	Technical Efficiency	AEZ	Technical Efficiency
1994	0.317	Tigray	0.464	Northern highlands	0.541
1999	0.345	Amhara	0.617	Enset (hoe)	0.127
2004	0.369	Oromia	0.458	Hararghe (oxen)	0.422
2009	0.412	SNNPR	0.127	Arussi-Bale	0.357
-	-	-	-	Central highlands	0.633
Average	0.362	-	0.362	-	0.362

Source: Author's calculation.

Results from the TFE efficiency analysis, presented in Table 3, show that both the northern and central highland AEZs have high technical efficiency and scores above the national average after controlling for AEZ differences. The enset farming, Hararghe oxen, and Arussi/Bale farming regions have efficiency scores below the national average. Precipitation is an important factor for Ethiopia's rainfed agriculture, more specifically in the northern highlands, which is a relatively dry region of the country. After controlling for AEZ differences, farms in the northern and central AEZs are more efficient than those in the other AEZs.

Moreover, Table 4 shows that the picture of technical efficiency observed with the TIE model is similar to that observed with the TFE model during the period studied across regions and AEZs. Table 4 also presents regional efficiency scores, showing that the Oromia, Tigray, and Amhara region scores are at or above the national average, whereas the SNNPR scores are lower.

5. Conclusions and Policy Suggestions

In Ethiopia, the agricultural sector plays an important role in the economy and is an essential source of food, employment, and income. Improving production efficiency is one way of satisfying the growing domestic food demand. There is substantial scope for increasing food production by improving the technical efficiency of farmers. This study shows that there is considerable room to increase domestic food supplies by improving management practices using existing inputs and technologies. Key factors for improving production efficiency in Ethiopia include factors that can be influenced by the market, the government, and farmers. Farm size, land quality, land fragmentation, age, education, family size, crop share, credit, extension service, and off-farm participation are the main factors affecting technical efficiency among smallholder Ethiopian farmers. The government can influence education and family size in the long run, and changes in crop shares, credit, extension service, off-farm participation, and technology use are quite rapid.

Education enhances farmers' managerial skills, including the efficient use of agricultural inputs. In the long term, education is important, both directly, as it increases technical efficiency, and indirectly, as it increases the value of off-farm employment. Hence, the government has to design supplementary education for farmers that enhances their efficiency.

It is difficult to increase farm size, at least in the short term, and one can hardly blame the government for land fragmentation, although land-use policies could be implemented in the longer term. Larger farms are more efficient than smaller farms. The average farm size in Ethiopia is approximately 1.5 ha, and the average number of plots is approximately 5, which shows that the farms are very small and highly fragmented. In the long term, land fragmentation can be improved by strengthening resettlement programs, and providing ownership rights to farmers. Hence, collective, modern farming and revised land ownership policy are vital to increasing farm efficiency.

It is found that households with large family sizes are likely to be technically inefficient. Hence, policies and strategies should be designed to expand and promote small enterprises and microenterprises in the country that can absorb excess labor from rural areas to reduce the negative effect of large family size on agricultural production efficiency. Furthermore, education on family planning should be strengthened by the government to reduce population pressures on scarce land resources in the long term.

There are microfinancial institutions in Ethiopia, although they are not yet sufficiently developed to reach the rural population. However, even in areas where rural financial institutions provide service, there are many bottlenecks that have to be addressed (timeliness of credit, amount of credit, collateral requirement, and repayment time) that will affect whether the hypothesis is supported. This is mainly because farmers (approximately 66%) divert credit from production to consumption. Training tailored to farmers on credit provision, usage, and repayment should be provided. Small enterprises and microenterprises in rural areas should be encouraged via rural credit. Considering that the reformation of sustainable rural financial institutions is a difficult task in poor rural economies, the study recommends a cautious and gradual strategy for the expansion of rural financial institutions in the country. This approach needs government support concerning legal and regulatory frameworks, institutionalized innovations, and pilot programs in rural areas that have the potential to reduce transaction costs by providing savings, credit, and insurance services to farmers.

This study shows that only 50% of the farmers received technical support in a given production year, meaning that the majority of the farmers did not receive any advice. Farmer training centers (FTCs) were initially planned to train farmers regarding practice in agronomy, animal and crop production, protection, input use (e.g., seeds feed, and fertilizer), soil conservation, and other activities. FTCs are still a viable and an effective approach for extending science-based knowledge and practices to farmers in Ethiopia. FTC training programs utilize participatory methods to help farmers develop their analytical skills, critical thinking, and creativity, and help them learn to make better decisions'. Furthermore, public investment in infrastructure (roads, transportation, and communication) is vital to improving extension service and smallholder farmers' technical efficiency.

Farming activities in Ethiopia are seasonal and demand labor during the growing season. Scheduling off-farm activity in the offseason of the production year can reduce the negative influence on technical efficiency. On the other hand, income generated from off-farm activity might be used for production purposes. Off-farm activity becomes advantageous if it is related to agricultural production that can help increase production and gain experience, such as irrigation farming.

Mixed farming benefits technical efficiency more than the specialization of either crop or animal production. As evidenced by crop share to total farm income, such farming improves technical efficiency. Crop and animal production complement each other with little competition. This implies the necessity of implementing strategies to integrate smallholder crop and livestock production and strengthen linkage to further improve the crop production efficiency of mixed crop-livestock farmers in Ethiopia. Moreover, policies and strategies should also support many agronomic practices, such as mixed farming, to improve soil fertility, thereby improving technical efficiency.

The current low level of technical efficiency can be addressed by increasing farmers' access to education, improving rural credit and extension services, enhancing fertilizer and improved seed use, promoting research and development, enhancing mixed farming, improving land quality, improving family planning, and promoting small-scale irrigation schemes.

Generally, Ethiopia must work in different directions to be food self-sufficient, such as utilizing irrigation farming and mechanized farming, with the help of agricultural research and development. Therefore, policies and strategies aimed at improving education, extension, credit, and input supply systems will help raise the technical efficiency and productivity of farmers.

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Appendix A. Description of the Study Area

This survey covers 18 farmer associations (FAs) in 15 of the 389 woredas[5] (districts) in the four major regions. ERHS data cover many villages in rural Ethiopia. One FA was selected from each of the woredas, except for one large woreda in the Amhara region, Debre Birhan, from which four FAs were included in the sample. The surveys were conducted with a sample stratified over the country's three major agricultural systems found in five agroecological zones (Dercon 2004).

The first agroecological zone is known as the northern highlands. This zone includes two villages in the Tigray region, Geblen and Harresaw, and one in the Amhara region, Shumsheha. The northern highlands are characterized by poor resource endowments, adverse climatic conditions, and frequent droughts.

The central highland agroecological zone is represented by the villages of Dinki, Yetmen, and Debre Birhan, all located in the Amhara region, and Turufe Ketchema in the Oromia region.

The Arussi/Bale agroecological zone includes the villages of Koro Degaga and Sirbana Godeti, both found in Oromiya. Adele Keke is the sole survey site found in the Hararghe agroecological zone of Oromiya.

The five remaining villages, Imdibir, Aze Deboa, Gara Godo, Adado, and Doma, are found in the enset-growing agroecological zone located in the Southern Nations, Nationalities and Peoples' Region. The ERHS datasets include data on household characteristics, agricultural production (plants and livestock), farm characteristics and other variables. Additional data from the National Meteorological Services Agency of Ethiopia are used.

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[5] A woreda is a governmental administrative unit below zone in the given region and equivalent to the district designation elsewhere.

Table A1. Definitions and units of measurement for variables in the stochastic frontier model.

Variable	Description	% With a Value of 1	Mean	SD	Min	Max
Sex	1 if the household head is male and 0 otherwise	79.87	-	-	-	-
Age	Age of the household head (years)	-	49.73	15.14	15	100
Education	1 if the household head is literate and 0 otherwise	38.46	-	-	-	-
Family size	Total number of family members	-	6.80	3.04	1	18
Farm size	Total farm size operated by the household (hectares)	-	1.51	1.18	0.01	6.38
Plot	Number of plots owned	-	5.03	2.95	1	29
Farm-plot	Farm-plot interaction/fragmentation (*timads*, quarter of a hectare)	-	1.40	1.36	0.005	25.5
Land quality	Soil fertility-slope interaction	-	6.49	2.29	1	9
Soil fertility	1 if the fertility status is good and 0 otherwise	47.08	-	-	-	-
Labor	Adult equivalent units	-	4.07	2.22	0.2	12.8
Output value	Sum of the real values of crops and livestock (birr)	-	3121.46	4211.12	1.33	46,089.34
Wealth/Assets	Sum of assets (birr)	-	16,220.74	39,288.96	0.00	510,947.9
Oxen	Number of oxen owned	-	1.00	1.01	0	5
Fertilizer	Total real value of fertilizer expenditure of the household (birr)	-	145.33	238.35	0.00	1255.62
Seeds	Total real value of seed expenditure of the household (birr)	-	325.81	852.94	0.00	13400
Credit	1 if the household uses credit and 0 otherwise	52.49	-	-	-	-
Extension	1 if the household is visited by an extension agent for technical support and 0 otherwise	50.40	-	-	-	-
Market distance	Market distance from home(minutes)	-	25.70	33.65	0.00	160
Hoe	1 if the household uses a hoe for farming and 0 otherwise	65.19	-	-	-	-
Off-farm income	1 if the household participates in off-farm income generation and 0 otherwise	41.86	-	-	-	-
Crop share	Proportion of crop income relative to total income(crops and livestock)	-	0.93	0.15	0.05	1
Agroecological zone (AEZ)	1for the northern highlands, 2 for the enset-growing area (hoe farming), 3 for Hararghe (oxen farming), 4 for Arussi/Bale and 5 for the central highlands	14, 33, 8, 13, 32	-	-	-	-
Precipitation	Rainfall amount (mm)	-	85.64	28.51	26.54	176.99

Source: Author's calculation. SD = standard deviation. Note: Monetary values are expressed in 1994 prices by using the producer price index.

The total value of outputs is calculated based on the yield and prices of the sample crops. This process enables us to aggregate and compares farm output and inputs within and between households. All value measures are expressed based on the 1994 prices using the producer price index for farm products and some of the inputs.

Table A2. Summary of input-output data used in the stochastic production frontier for 1994–2009.

Production Year	Variables	Output (birr)	Land (ha)	Labor (AEU)	Draft Power (oxen)	Assets (birr)	Fertilizer (birr)	Precipitation (mm)	Seeds (birr)	Hoe Dummy	Soil Fertility Dummy
1994	Mean	1907.01	1.44	5.11	0.62	24,198.92	49.94	88.26	312.08	0.60	0.37
	Median	1053.84	1.06	4.84	0.00	6360.79	0.00	82.63	50.00	1.00	0.00
	Max	23,126.52	6.25	12.80	5.00	447,276.30	1056.36	159.50	7671.00	1.00	1.00
1999	Mean	2783.10	1.28	5.11	1.14	16,239.11	159.86	88.38	330.23	0.47	0.51
	Median	1997.50	1.00	4.94	1.00	5141.94	57.03	81.15	54.00	0.00	1.00
	Max	33,639.82	6.00	12.78	5.00	459,107.20	1197.88	143.79	9705.00	1.00	1.00
2004	Mean	3680.34	1.59	3.66	1.00	16,153.67	166.62	80.40	325.28	0.73	0.47
	Median	1774.56	1.25	3.40	1.00	4327.79	0.00	82.62	50.00	1.00	0.00
	Max	46,089.34	6.38	11.60	5.00	510,947.90	1255.62	176.99	13,400.00	1.00	1.00
2009	Mean	4006.99	1.74	2.48	1.23	8848.75	197.64	86.03	334.77	0.79	0.54
	Median	2591.46	1.38	2.40	1.00	2190.63	43.64	78.89	52.00	1.00	1.00
	Max	42,175.59	6.38	8.00	5.00	249,388.70	1247.21	129.90	13,400.00	1.00	1.00
Total	Mean	3121.46	1.51	4.06	1.00	16,220.74	145.33	85.64	325.81	0.65	0.47
	Median	1789.32	1.25	3.70	1.00	4101.18	0.00	82.06	51.80	1.00	0.00
	Max	46,089.34	6.38	12.80	5.00	510,947.90	1255.62	176.99	13,400.00	1.00	1.00

Source: Author's calculation.

Table A3. Robustness check of parameter estimates from cobb-douglas stochastic frontier analysis under true fixed and time-varying inefficiency effects models by removing hoe and assets.

True Fixed Effect (TFE) Model: Controls for Observed and Unobserved Heterogeneity				Time-Varying Inefficiency Effects (TIE) Model		
Variables	**Estimate**	**SE**	**Z-Test**	**Estimate**	**SE**	**Z-Test**
lnx1 (Farm size)	0.124 ***	5.28×10^{-5}	2347.78	0.422 ***	0.030	13.88
lnx2 (Labor)	0.342 ***	4.85×10^{-5}	7046.36	0.119 ***	0.025	4.74
lnx3 (Oxen)	0.038 ***	1.73×10^{-5}	2217.46	0.050 ***	0.004	12.69
lnx5 (Precipitation)	0.561 ***	4.15×10^{-5}	1.4×10^{4}	0.128 ***	0.047	2.72
lnx6 (Seeds)	0.048 ***	2.09×10^{-5}	2291.90	0.035 ***	0.006	6.25
lnx7 (Fertilizer)	0.005 ***	1.32×10^{-5}	667.92	0.017 ***	0.002	7.50
x10 (Soil fertility dummy)	0.029 ***	13.56×10^{-5}	214.32	0.210 ***	0.039	5.43
x11 (AEZ)		Northern highlands				
Enset, hoe	4.525 ***	18.75×10^{-5}	2.4×10^{4}	4.153	2.716	1.53
Hararghe, oxen	3.071 ***	22.54×10^{-5}	1.4×10^{4}	0.926 ***	0.140	6.58
Arussi/Bale	2.900 ***	21.59×10^{-5}	1.3×10^{4}	0.745 ***	0.137	5.42
Central highlands	2.668 ***	23.29×10^{-5}	1.1×10^{4}	0.288 ***	0.079	3.63
T (years)	0.244 ***	5.22×10^{-5}	4662.99	0.022	0.023	0.96
Exogenous inefficiency determinants						
δ1 (Gender)	0.394	0.793	0.50	−0.304 ***	0.070	−4.38
δ2 (Age)	−0.243 *	0.146	−1.66	0.002	0.010	0.19
δ3 (Age2)	0.002 *	0.001	1.64	−0.000	0.000	−0.62
δ 4 (Education dummy)	−1.14 *	0.720	−1.59	−0.253 ***	0.059	−4.28
δ5 (Family size)	0.270 **	0.110	2.44	−0.025 **	0.010	−2.58
δ6 (Farm size)	−0.662 ***	0.139	−4.76	−0.011	0.013	−0.83
δ7 (Land quality index)	−0.262 **	0.140	−1.87	0.003	0.017	0.21
δ8 (Land fragmentation)	0.979 ***	0.268	3.65	0.195 ***	0.021	9.34
δ9 (Credit dummy)	1.558 **	0.653	2.39	0.290 ***	0.054	5.38
δ10 (Extension dummy)	−0.604 *	0.306	−1.73	−0.059 **	0.024	−2.48
δ11 (Market distance)	0.003	0.009	0.03	−0.005 ***	0.001	−5.06
δ12 (Off-farm income dummy)	1.224 *	0.635	1.93	0.137 ***	0.054	2.52
δ13 (Crop share)	−5.091 ***	1.935	−2.63	−0.484 ***	0.180	−2.69

Table A3. *Cont.*

	True Fixed Effect (TFE) Model: Controls for Observed and Unobserved Heterogeneity			Time-Varying Inefficiency Effects (TIE) Model		
Variables	**Estimate**	**SE**	**Z-Test**	**Estimate**	**SE**	**Z-Test**
δ14 (AEZ)	Northern highlands					
Enset, hoe	12.747 ***	2.108	6.05	5.341 *	2.736	1.95
Hararghe, oxen	8.434 ***	2.064	4.08	1.404 ***	0.371	3.78
Arussi/Bale	13.104 ***	2.603	5.04	2.072 ***	0.330	6.27
Central highlands	5.959 **	2.391	2.49	0.531	0.332	1.60
T (years)	0.040	0.663	0.06	0.133 *	0.071	1.87
δ16 (AEZ-t interaction)	−0.357 *	0.209	−1.71	−0.133 ***	0.028	−4.80
Constant	−12.064 ***	3.574	−3.38	0.384	0.504	0.76
Sigma(u)constant	2.760 ***	0.163	16.91	0.010	0.054	0.19
Sigma(v)constant	−29.179 *	15.519	−1.88	−0.977 ***	0.082	−11.90
Sigma(u): δ_u^2	3.976 ***	0.324	12.25	1.005 ***	0.027	37.24
Sigma(v): δ_v^2	4.57×10^{-7}	3.55×10^{6}	0.13	0.614 ***	0.025	24.37
Lambda: $\lambda = \frac{\delta_u^2}{\delta_v^2}$	1.39×10^{7} ***	0.312	4.5×10^{7}	1.638 ***	0.044	37.50
Gamma:$\gamma = \frac{\delta_u^2}{\delta_u^2+\delta_v^2}$	0.999	-	-	0.621	-	-
Wald chi2 (12) *p*-value	1.55×10^{10}	-	-	754.97	-	-
Prob. chi2	0.000	-	-	0.000	-	-
Log likelihood function	−3387.97	-	-	−6044.57	-	-
Number of households	1195	-	Observations	4496	-	-

Source: Author's calculation. SE = standard error, *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A4. Robustness check of parameter estimates from cobb-douglas stochastic frontier analysis under true fixed and time-varying inefficiency effects models by squaring farm size.

True Fixed Effect (TFE) Model: Controls for Observed and Unobserved Heterogeneity				Time-Varying Inefficiency Effects(TIE) Model		
Variables	**Estimate**	**SE**	**Z-Test**	**Estimate**	**SE**	**Z-Test**
lnx1 (Farm size squared)	0.062 ***	0.008	8.20	0.209 ***	0.015	14.37
lnx2 (Labor)	0.301 ***	0.006	50.17	0.107 ***	0.025	4.31
lnx3 (Oxen)	0.041 ***	0.016	2.61	0.045 ***	0.004	11.25
lnx5 (Precipitation)	0.510 ***	0.023	21.95	0.138 ***	0.046	2.98
lnx6 (Seeds)	0.042 *	0.023	1.85	0.034 ***	0.006	6.02
lnx7 (Fertilizer)	0.006 ***	0.001	8.78	0.017 ***	0.002	7.66
x8 (Hoe dummy)	0.080 ***	0.050	1.60	0.155 ***	0.031	4.97
lnx9 (Assets)	0.077 ***	0.039	19.91	0.031 ***	0.006	4.82
x10 (Soil fertility index)	0.016	0.024	0.69	0.220 ***	0.038	5.79
x11 (AEZ)		Northern highlands		-	-	-
Enset, hoe	4.543 ***	0.048	95.39	4.378	3.994	1.10
Hararghe, oxen	2.850 ***	0.019	153.46	0.921 ***	0.137	6.72
Arussi/Bale	2.644 ***	0.170	15.59	0.708 ***	0.133	5.32
Central highlands	2.414 ***	0.016	151.55	0.269 ***	0.079	3.41
T (years)	0.226 ***	0.006	35.97	0.021	0.023	0.91
Exogenous inefficiency determinants		-	-	-	-	-
δ1 (Gender)	0.246	0.750	0.33	−0.279 ***	0.071	−3.92
δ2 (Age)	−0.242 *	0.132	−1.84	0.002	0.011	0.22
δ3 (Age2)	0.002 *	0.001	1.80	−0.000	0.000	−0.60
δ 4 (Education dummy)	−1.326 *	0.689	−1.92	−0.239 ***	0.060	−3.99
δ5 (Family size)	0.258 **	0.104	2.49	−0.021 **	0.010	−2.19
δ6 (Farm size)	−0.707 ***	0.136	−5.21	−0.010	0.013	−0.78
δ7 (Land quality index)	−0.279 **	0.143	−1.96	0.003	0.017	0.15
δ8 (Land fragmentation)	1.034 ***	0.257	4.02	0.194 ***	0.021	9.10
δ9 (Credit dummy)	1.214 **	0.602	2.02	0.282 ***	0.054	5.21
δ10 (Extension dummy)	−0.504 *	0.301	−1.68	−0.059 **	0.024	−2.47
δ11 (Market distance)	0.008	0.009	0.89	−0.005 ***	0.001	−4.96
δ12 (Off-farm income dummy)	1.183 *	0.618	1.91	0.165 ***	0.055	2.98
δ13 (Crop share)	−4.882 ***	1.865	−2.62	−0.512 ***	0.182	−2.81

Table A4. *Cont.*

Variables	True Fixed Effect (TFE) Model: Controls for Observed and Unobserved Heterogeneity Estimate	SE	Z-Test	Time-Varying Inefficiency Effects(TIE) Model Estimate	SE	Z-Test
δ14 (AEZ)	Northern highlands		-	-	-	-
Enset, hoe	11.991 ***	1.958	6.13	5.702	4.009	1.42
Hararghe, oxen	8.568 ***	1.988	4.31	1.541 ***	0.386	3.99
Arussi/Bale	13.507 ***	2.506	5.39	2.242 ***	0.346	6.49
Central highlands	7.231 ***	2.289	3.16	0.724 **	0.353	2.05
T (years)	0.032	0.630	0.05	0.162 **	0.074	2.19
δ16 (AEZ-t interaction)	−0.477 **	0.199	−2.39	−0.148 ***	0.029	−5.03
Constant	−10.462 ***	3.420	−3.06	0.151	0.511	0.30
Sigma(u)constant	2.712 ***	0.153	17.69	−0.007	0.055	−0.12
Sigma(v)constant	−28.179 *	15.701	−1.79	−0.946 ***	0.077	−12.22
Sigma(u): δ_u^2	3.881 ***	0.298	13.04	0.997 ***	0.027	36.42
Sigma(v): δ_v^2	7.60×10^{-7}	5.97×10^{-6}	0.13	0.623 ***	0.024	25.82
Lambda: $\lambda = \frac{\delta_u^2}{\delta_v^2}$	5.10×10^{6} ***	0.298	1.7×10^{7}	1.599 ***	0.044	36.76
Gamma:$\gamma = \frac{\delta_u^2}{\delta_u^2+\delta_v^2}$	0.999	-	-	0.615	-	-
Wald chi2 (14) *p*-value	6.92×10^{-9}	-	-	868.87	-	-
Prob. chi2	0.000	-	-	0.000	-	-
Log likelihood function	−3425.59	-	-	−6019.58	-	-
Number of households	1195	-	Observations	4496	-	-

Source: Author's calculation. SE = standard error, *** significant at the 1% level; ** significant at the 5%level; * significant at the 10% level.

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