Vol. 15(1), pp. 19-32, January, 2020
DOI: 10.5897/AJAR2019.14601
Article Number: AE5BE3462625
ISSN: 1991-637X

http://www.academicjournals.org/AJAR

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African Journal of Agricultural Research

Full Length Research Paper

Sources of productivity growth in Ethiopian agriculture

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Received 19 November, 2019; Accepted 11 December, 2019

In Ethiopia, agricultural production and productivity are very low, and hence increase in production and productivity are vital to meet increasing food demand. This study identifies and quantifies the main sources of productivity growth in Ethiopian agriculture using the translog (TL) stochastic input distance function and the Ethiopian Rural Household Survey (ERHS) panel dataset. The true fixed effects (TFE) panel data estimator is used to separate inefficiency effects from observed and unobserved heterogeneity. The parametric Malmquist productivity index (MPI) is used to decompose total agricultural growth into three major sources. The average technical efficiency score was 0.875; this finding indicates that on average a farmer produces 87.5% of the value of the output that is produced by the most efficient farmer using the same technology and inputs. This implies that they can reduce the inputs required to produce the average output by 12.5% if their farming operation becomes technically efficient. MPI shows that the average annual productivity growth was 17.9% between 1994 and 2009. Further decomposition of the index shows that scale efficiency change is the most important source of this growth, and accounts for about 14.5%. Technological improvement accounts for approximately 4.8% while the contribution of technical efficiency change is negative, leading to an annual productivity decline of 1.3%. This finding suggests that increasing productivity is possible via improving these components by improving training to the farmers, extension services, research and development, and agronomic practices.

Key words: Productivity growth, translog stochastic input distance function, Malmquist productivity index, Ethiopia.

INTRODUCTION

Ethiopia is the second most populated country (109.2 million) in Africa, with the gross domestic product (GDP) of 84.4 billion USD, 7.6% GDP growth, 9.6% inflation, and 2.5% population growth as of 2018. Agriculture is a major economic activity in many developing countries. Ethiopia is no exception as it is predominantly an agrarian economy. Agriculture accounts for about 50% of GDP, 85% of employment, 70% of raw materials for

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JEL codes: D13; O12; O13; O33; O47; Q12; Q18.

industry, and 90% of foreign earnings. Agricultural production of crops and livestock are the main sources of income and employment for 70% of its rural population (World Bank, 2018a, b). The government aims to transform the economy of Ethiopia into a middle-income country by 2025. Thus, agriculture is part of this transformation with substantial growth in production and productivity. The population grows fast while the amount of cultivable land remains constant to produce food and fiber to the growing population. Thus, improving productivity in the agricultural sector is an important step forward to meet food supply challenges and to generate more income in rural areas. Total factor productivity (TFP) change is an important notion in developing countries because it measures the ability of households, firms, industries, and national economies to enhance the aggregate volume of outputs given the aggregate volume of inputs used (Balk et al., 2019).

Increasing agricultural productivity is one way to meet this growing demand. Improvements in agricultural productivity are also vital for economic development, especially in developing countries. In developing countries with low productivity, such as Ethiopia, there is limited surplus production over and above household consumption, which restricts market supply.

To my knowledge, there are no rigorous empirical studies that investigate sources of productivity growth in Ethiopia. To assess low agricultural productivity, we need to identify and quantify the main sources of productivity growth. In the literature, the main components of productivity growth include technical change and efficiency change. Efficiency change can be further decomposed into technical, mix and scale efficiency change (O'Donnell, 2012). O'Donnell (2016) states that the total factor productivity (TFP) index can be theoretically decomposed into measures of environmental change, technical change and other sources of efficiency change (technical, mix (input and/or output), and scale efficiency change). Kumbhakar et al. (2015) argue that most of a company's efficiency improvements come from technical efficiency improvements and technological improvements. Technical efficiency change means that the individual farmer moves closer to or further away from the boundary while technological improvement means that the set of feasible combinations expands or contracts (Balk, 2001). Scale efficiency measures the gap between constant and variable (increasing and decreasing) returns to scale. Therefore, scale efficiency change refers to the productivity growth that will arise because of a producer operating at a scale closer to the most productive scale size (MPSS) (Färe et al., 1994b). In comparison, mix efficiency is a measure of productivity change that arises when the input and/or output mix restrictions are relaxed, leading to an increase in the set of feasible input and/or output combinations (O'Donnell, 2012).

In agriculture, the three main sources of productivity growth are technological improvement, technical efficiency improvement, and scale efficiency change. Some nomenclatures are:

(1) Technical efficiency improvements essentially refer to increases in output-input ratios by reducing slack in the production process.
(2) Technological improvements usually refer to the expansion of a set of production possibilities that result from increased knowledge.
(3) Scale efficiency change refers to working at a scale level that is closer to the maximum productive scale size (Färe et al., 1994b).

Policies that are designed to improve agricultural productivity can target these different components. Such policies that are designed to increase productivity through improvements in technical efficiency include education, training and extension programs. Policies that seek to improve productivity through technical progress include government support for investment in scientific research and development. Policies that assist farmers to operate a scale closer to the most productive scale size include relaxing restrictions on land ownership and transfer, recommending proper input and/or output combination based on orientation and returns to scale. For example, if a producer is operating at decreasing returns to scale, then the scale of production can be optimized by a reduction of input(s).

There are limited empirical literatures measuring and decomposing productivity growth in Ethiopian agriculture. A summary of the various thematic strands of this empirical research are:

(1) Productivity comparisons between farmers who use an extension package program and those who do not (Ayele et al., 2006), or ways in which productivity can reduce the poverty of smallholder farmers (Abro et al., 2014).
(2) Assess the impact of sustainable agricultural practices (minimum tillage) (Kassie et al., 2011), or the effects of soil and water conservation (Adgo et al., 2013) on crop productivity.
(3) The effects of inefficiency as an explanatory variable on supply response using a profit function approach (Abrar and Morrissey 2006), and estimate and compare inefficiency from stochastic frontier analysis (SFA) with ordinary least square (OLS) during 1994 to 2004 (Bachewe, 2009). This paper covers a longer time (1994 -2009) than Bachewe (2009).

Methodologically, these studies employed the Tornqvist index (Ayele et al., 2006), propensity score matching methods and a switching regression model (Kassie et al., 2011), a macroeconomic approach to the growth accounting method (Bachewe, 2012), or stochastic frontier analysis (SFA) (Abro et al., 2014; Bachewe, 2009). Most previous studies did not include risk and animal products and employed deterministic approaches. Besides, the model specifications in the parametric SFA approach used by these studies do not separate technical inefficiency and unobserved heterogeneity. Consequently, technical inefficiency might be over-estimated, and hence conclusions might be biased.

Moreover, these studies do not decompose productivity growth into its components. They neither disaggregate of crop and livestock products nor use multiple-input multiple-output (MIMO) approaches. Only a few of these studies use panel data, and when they do, the panels span short periods.

Finally, these few studies on productivity growth in Ethiopian agriculture are narrow in scope. Most of them only consider crop products, use cross-sectional data, shorter panel, and small sample sizes.

In comparison, this study employs modern methods on a large panel data set that contributes to the literature in the following ways. First, a comprehensive understanding of the main components of productivity growth can help to make Ethiopian agricultural policy more focused. This study contributes to this end by investigating the sources of agricultural productivity growth in Ethiopia into three major components. Second, it includes the risk preference behavior of households in the production function. Third, it takes into account livestock products separately from crop products by using a multi-out procedure using distance function techniques to give equal attention to crop and animal products. Fourth, it uses a true fixed effects (TFE) model that enables one to separate observed and unobserved heterogeneity from inefficiency.

Fifth, it simultaneously estimates production technology and inefficiency. Sixth, it employs a stochastic frontier approach with a longer panel. Last of all, it employs total agricultural productivity decomposition rather than the extant literature of partial agricultural productivity.

METHODOLOGY

This part discusses Input Distance Function (IDF), Malmquist Productivity Index (MPI), econometric specification of IDF, and data sources and collection precisely.

Input distance function

For a vector of inputs $\boldsymbol{X} = x_1, x_2, \ldots, x_k$ and a vector of outputs, $\boldsymbol{Y} = y_1, y_2, \ldots, y_m$, the multiple input-output production technology defined by T. The technology set T is defined as an input-output relationship given as follows:

$$T = \{(\xi, \psi): x \text{ can produce } \psi\}, \quad (1)$$

Where, $\xi \in \Re_+^K$ is a vector of K inputs and $\psi \in \Re_+^M$ is a vector of M outputs of non-negative real numbers. This technology can be consistently represented using the input requirement set $\Lambda(\psi) = \{\xi:(\xi, \psi) \in T\}$. This input requirement set requires a technology that satisfies strong disposability[1] of inputs, and is closed and convex for all outputs (Coelli et al., 2005). The distance function measures the distance between a particular observation $(\xi, \psi) \in \Re_+^K \times \Re_+^M$ and the efficient technology boundary. Its value depends on a mapping rule, or a directional vector, which determines the direction in which the inputs are to be contracted and/or the outputs are to be expanded to reach this efficient boundary. The input distance function (IDF) $D_I(x, y)$ defined on the technology set given as:

$$D_I(x, y) = \max_\lambda\{\lambda \geq 1: \frac{\boldsymbol{X}}{\lambda} \boldsymbol{\epsilon}\, L(y)\}, \quad (2)$$

Where, λ is an input scaling factor by which the inputs can be contacted to make them technically efficient given the outputs. Concerning inputs, IDF $D_I(x, y)$ is non-decreasing, homogenous of degree one, and concave, whereas with respect to outputs, IDF$D_I(x, y)$ is non-increasing and quasi-concave (Färe and Primont, 1990). Further, IDF $D_I(x, y) \geq 1$ when the input mix is feasible or $\boldsymbol{X} \in L(y)$, whereas IDF $D_I(x, y) < 1$ when the input mix is infeasible or $\boldsymbol{X} \notin L(y)$. Therefore, for any feasible production mix, the technical efficiency (TE) is computed from IDF as:

$$\mathrm{TE} = \frac{1}{\mathrm{D_I(x,y)}} \quad (3)$$

Since, IDF $D_I(x, y) \geq 1$ for any data points, then $0 \leq TE \leq 1$ for any feasible observation. Both TE and IDF are equal to one when a household produces on the frontier for technically efficient households, and TE tends to zero as IDF tends to infinity for technically inefficient households.

The IDF, following input-output vector (x_i^t, y_i^t) , and the exogenous environmental variables, $z_i^t = z_{i,1}^t, \ldots, z_{i,q}^t$ is given as:

$$D_I^t(x_i^t, y_i^t) = F\left[\left(x_{i,1}^t, \ldots, x_{i,k}^t, y_{i,1}^t, \ldots, y_{i,m}^t\right), z_{i,q}^t, t\right] \quad (4)$$

$$\frac{1}{x_{i,r}^t} = F\left[\left(\frac{x_{i,1}^t}{x_{i,r}^t}, \ldots, 1, \ldots, \frac{x_{i,k}^t}{x_{i,r}^t}, y_{i,1}^t, \ldots, y_{i,m}^t\right), z_{i,q}^t, t\right] / D_I^t(x_i^t, y_i^t) \quad (5)$$

Following Orea (2002), F is a flexible translog (TL) technology proposed by Christensen et al. (1973). It is a more general and flexible functional form than Cobb-Douglas (CD) model. The TL approximation to the input based distance function is given as:

$$\begin{aligned} -lnx_{r,i,t}^t = \alpha_i \; + \; & \sum_{k=1}^{K-1} \beta_k \, lnx_{i,k}^{*t} + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{j=1}^{K-1} \beta_{k,j} \, lnx_{i,k}^{*t} lnx_{i,j}^{*t} \\ & + \sum_{m=1}^{M} \theta_m \, lny_{i,m}^t + \frac{1}{2}\sum_{m=1}^{M}\sum_{j=1}^{M} \theta_{m,n} \, lny_{i,m}^t lny_{i,n}^t \\ & + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \phi_{m,k} \, lny_{i,m}^t lnx_{i,k}^{*t} + \Upsilon_1 t + \frac{1}{2}\Upsilon_2 t^2 \\ & + \sum_{m=1}^{M} \psi_m t lny_{i,m}^t + \sum_{k=1}^{K-1} \eta_k t lnx_{i,k}^{*t} \\ & + \sum_{p=1}^{P} \xi_p z_{i,q}^t - u_{i,t} + v_{i,t} \end{aligned} \quad (6)$$

Where, $lnx_{i,k}^{*t} = lnx_{i,k}^t - lnx_{i,r}^t$, $v_{i,t}$ is the stochastic noise term, α_i is unobserved heterogeneity, and $u_{i,t} = lnD_I^t(x_i^t, y_i^t))$ is a non-negative error term capturing time-varying inefficiency. There are k

[1] The strong disposability assumption in inputs states that a proportional increase in inputs cannot decrease outputs (Färe et al., 1985; 1994a).

inputs and m outputs. Homogeneity of degree one in input quantities implies that:

$$\sum_{k=1}^{K}\beta_k = 1 \quad and \quad \sum_{K}^{K}\beta_{k,j} = \sum_{K}^{K}\phi_{m,k} = \sum_{K}^{K}\eta_k = 0 \tag{7}$$

Whereas, quadratic symmetry implies $\beta_{k,j} = \beta_{j,k}$ and $\theta_{m,n} = \theta_{n,m}$. These restrictions are imposed before estimating IDF above by dividing the quantity of all inputs is divided by the quantity of oneof the inputs (Lovell et al., 1994). The method also allows the IDF to be estimated as it gives equation (6). Monotonicity requires all estimated IDF elasticities to satisfy the following conditions.

$$\frac{\partial lnD_I^t(.)}{\partial lny_m^t} = \theta_m + \sum_{m=1}^{M}\theta_{m,n}\, lny_n^t + \sum_{k=1}^{K-1}\phi_{m,k} lnx_{i,k}^{*t} + \psi_m t \leq 0$$

and

$$\frac{\partial lnD_I^t(.)}{\partial lnx_k^{*t}} = \beta_k + \sum_{k=1}^{K-1}\beta_{k,j}\, lnx_{k,j}^{*t} + \sum_{m=1}^{M}\phi_{m,k} lny_m^t + \eta_k t \geq 0 \tag{8}$$

Saal et al. (2007) noted that there are two features that the above IDF differs from the standard translog approximation: (1) The addition of q exogenous operating characteristics, whose impact on input requirements is captured in the term $\sum_{p=1}^{p}\xi_p z_{i,q}^t$. (2) The additional household-specific intercept instead of the single intercept parameter that is the heterogeneous household-specific α_i parameters. These fixed effects allow controlling further for factors influencing input requirements that have not been specifically controlled for in the model.

Malmquist productivity index

Caves et al. (1982a; b) demonstrate that the Malmquist (1953) index can be used to measure the growth in productivity that occurred between two periods based on a given reference technology. The reference technology can be represented by the technology of one of the periods, as constructed from the observed input-output data or by some combination of technologies from both periods. For example, Färe et al. (1992) defined the input-oriented MPI, M_I^{CCD}, as the geometric mean of the Malmquist productivity indices for two adjacent periods, t and $t+1$, as:

$$M_I^{CCD}(x^t, x^{t+1}, y^t, y^{t+1}) = M_I^t(x^t, y^t, x^{t+1}, y^{t+1}) \times M_I^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) \tag{9}$$

$$= \left[\frac{D_I^t(x^t, y^t)}{D_I^t(x^{t+1}, y^{t+1})} \times \frac{D_I^{t+1}(x^t, y^t)}{D_I^{t+1}(x^{t+1}, y^{t+1})}\right]^{\frac{1}{2}}$$

Where, (x^t, y^t) and (x^{t+1}, y^{t+1}) are input and output vectors that correspond to t and $t+1$, $D_I^t(.)$ and $D_I^{t+1}(.)$ are corresponding IDFs, and $M_I^t(.)$ and $M_I^{t+1}(.)$ are the respective Malmquist indices. It is possible to decompose the $M_I^{CCD}(.)$ index into technical efficiency change (that is catching up the best practice frontier), and technical change (that is a shift in the best practice frontier) (Saal et al., 2007; Fuentes et al., 2001; Färe et al., 1992). As indicated in Coelli et al. (2005), technical efficiency change between two periods can be expressed as:

$$M_I^I(x^t, x^{t+1}, y^t, y^{t+1}) = \frac{D_I^t(x^t, y^t)}{D_I^t(x^{t+1}, y^{t+1})} = \triangle\,\mathrm{TE}(x^t, x^{t+1}, y^t, y^{t+1}) = \frac{TE^{t+1}}{TE^t} \tag{10}$$

Given that $D_I^t(.) \geq 1$ for any feasibleinput-output mix, and $D_I^t(.)<1$for any infeasible input-output mix,$M_I^{CCD}(.)$can be less than ,equal to, or greater than one to indicate productivity progress, stagnation, or decline, respectively.

This study follows that of Orea (2002), who suggested a parametric decomposition of the Malmquist productivity index that enables scale efficiency change to be introduced without computing scale efficiencies. For translog specifications, ODF (Orea, 2002) and IDF (Saal et al., 2007) defined the parametric MPI as the weighted difference between the average growth rates of output and inputs. Following Orea (2002) and Balk (2001) of an ODF, and Saal et al. (2007) and Pantzios et al. (2011) of an IDF, for a translog specification, the parametric MPI can be defined using distance elasticities with respect to inputs and outputs as weights. These weights are derived from estimated translog IDF elasticities with respect to outputs and inputs evaluated with data at time t and $t+1$ as

$$lnM_I = -\frac{1}{2}M_I^t\sum_{m=1}^{M}[(\mathcal{E}_m^{t+1} + \mathcal{E}_m^t)(lny_m^{t+1} - lny_m^t)] - \frac{1}{2}M_I^t\sum_{j=1}^{J}\left[\left(\mathcal{E}_j^{t+1} + \mathcal{E}_j^t\right)\left(lnx_j^{t+1} - lnx_j^t\right)\right] \tag{11}$$

Where, $\mathcal{E}_m^t = \frac{\partial lnD_I^t(.)}{\partial lny_m}$ and $\mathcal{E}_j^t = \frac{\partial lnD_I^t(.)}{\partial lnx_j}$ indicate the output and input change weights evaluated at time t data, respectively, whereas $\mathcal{E}_m^{t+1} = \frac{\partial lnD_I^{t+1}(.)}{\partial lny_m}$ and $\mathcal{E}_j^{t+1} = \frac{\partial lnD_I^{t+1}(.)}{\partial lnx_j}$ are evaluated at time $t+1$ data points. The negative sign before the output change and input change indices are to ensure positive weights.

The input weights sum to one because the IDF is homogenous of degree one in input quantities. However, the sum of the output weights does not equal one except under constant returns to scale. This implies that equation (11) violates the proportionality property that is required to satisfy to be a total factor productivity index (Orea, 2002). This is because the elasticity of scale, that is returns to scale (RTS), is measured for the IDF representation of technology by the negative of the inverse of the sum of the output elasticities (Färe and Primont, 1995).

$$RTS^t = -\left(1\Big/\sum_{m=1}^{M}\mathcal{E}_m^t\right) \tag{12}$$

To ensure that the proportionality property is satisfied, the study follows that of Orea (2002) and define the output weights as elasticity shares. From Orea (2002) and Saal et al. (2007), the generalized parametric MPI is given as:

$$lnG_I = -\frac{1}{2}\sum_{m=1}^{M}\left(\left(\mathcal{E}_{m=1}^{t+1}\Big/\sum_{m=1}^{M}\mathcal{E}_m^{t+1}\right) + \left(\mathcal{E}_{m=1}^{t}\Big/\sum_{m=1}^{M}\mathcal{E}_m^{t}\right)\right)ln(y_m^{t+1}/y_m^t) - \frac{1}{2}M_I^t\sum_{j=1}^{J}\left[\left(\mathcal{E}_j^{t+1} + \mathcal{E}_j^t\right)\left(lnx_j^{t+1} - lnx_j^t\right)\right] \tag{13}$$

By rearranging Equation (13), Saal et al. (2007) showed that it is possible to write the generalized parametric MPI as:

$$lnG_I = lnM_I + \frac{1}{2}M_I^t\sum_{m=1}^{M}\left((\mathcal{E}_m^{t+1}SF_I^{t+1}) + (\mathcal{E}_m^t SF_I^t)\right)ln(y_m^{t+1}/y_m^t) \quad (14)$$

Where, $SF_I^t = ((\sum_{m=1}^{M}\mathcal{E}_m^t + 1)/\sum_{m=1}^{M}\mathcal{E}_m^t) = 1 - RTS^t$ is an input distance scale factor and RTS^t is the elasticity of scale at time *t*, as defined above. Thus, with constant returns to scale $RTS^t = 1$, $SF_I^t = 0$, and the generalized productivity index is equivalent to the Malmquist index. In contrast, with increasing (decreasing) returns to scale RTS>1 (RTS<1), and consequently$SF_I^t < 0(SF_I^t > 0)$, and the generalized productivity index captures the positive (negative) impact of change in scale on productivity growth, which are not captured by MPI.

Orea (2002) used the quadratic identity (approximation) lemma of Diewert (1976) to decompose Equation 14 into the different components contributing to productivity growth. Following Diewert (ibid.), the quadratic identity lemma states that if F(s) is a quadratic function of its arguments, which is a vector of dimension R, then $F(S^1) - F(S^0) = \sum_{r=1}^{R}\frac{1}{2}[F_r(s^1) + F_r(s^0)][s^1 - s^0]$. In this equation, the superscripts on *s* represent certain data points (for example specific years), and $F_r = \frac{\partial F}{\partial S_r}$. In addition, $F(S^1)$ and $F(S^0)$ represent the evaluation of F_r at two data points. Since the translog functional form is quadratic in the natural logarithms of its arguments, the difference between the evaluations of the IDF at two data points, which is a decomposition of total productivity growth, can be written as follows:

$$-ln\left(\frac{D_I^{t+1}(.)}{D_I^t(.)}\right) \equiv -\frac{1}{2}\sum_{m=1}^{M}\left(\mathcal{E}_j^{t+1} + \mathcal{E}_j^t\right)\ln(y_m^{t+1}/y_m^t)$$
$$-\frac{1}{2}\sum_{j=1}^{J}\left(\mathcal{E}_j^{t+1} + \mathcal{E}_j^t\right)\ln(x_m^{t+1}/x_m^t)$$
$$-\frac{1}{2}\left({\partial lnD_I^{t+1}(.)}/{\partial t} + {\partial lnD_I^t(.)}/{\partial t}\right) \quad (15)$$

As the input distance is the negative inverse of the input based technical efficiency, i.e.,$-lnD_I^t = lnTE_I^t$, one can rewrite Equation 14 as:

$$lnG_I = [lnTE_I^{t+1} - lnTE_I^t]$$
$$+ \frac{1}{2}[(\partial lnD_I^{t+1}/\partial t) + (\partial lnD_I^t/\partial t)]$$
$$+\frac{1}{2}\sum_{m=1}^{M}\left((\mathcal{E}_m^{t+1}SF_I^{t+1}) + (\mathcal{E}_m^t SF_I^t)\right)ln(y_m^{t+1}/y_m^t) \quad (16)$$

Therefore, one can decompose Equation 14 into three sources of productivity growth:

(1) Change in technical efficiency $\Delta TE = lnTE_I^{t+1} - lnTE_I^t$,
(2) technical change $\Delta TC = +\frac{1}{2}[(\partial lnD_I^{t+1}/\partial t) + (\partial lnD_I^t/\partial t)]$, and
(3) Scale change $\Delta SC = +\frac{1}{2}\sum_{m=1}^{M}\left((\mathcal{E}_m^{t+1}SF_I^{t+1}) + (\mathcal{E}_m^t SF_I^t)\right)ln(y_m^{t+1}/y_m^t)$.

Technical changes are the derivatives of the IDF with respect to the time trend evaluated with data at periods *t* and *t+1*. Thus, total factor productivity growth ($TFPG^{t,t+1}$) is the sum of technical efficiency change ($EC^{t,t+1}$), technical change ($TC^{t,t+1}$), and scale change($SC^{t,t+1}$) between *t* and *t+1* periods as:

$$TFPG^{t,t+1}=EC^{t,t+1}+ TC^{t,t+1}+ SC^{t,t+1} \quad (17)$$

Econometric specification

The translog IDF specified in Equation 6 was estimated using stochastic frontier analysis (SFA). The stochastic frontier production function framework independently introduced by Aigner et al. (1977), and Meeusen and Van den Broeck (1977) and latterly developed by Greene (2005a, b). The parametric SFA is employed to take account of the effect of measurement error and stochastic noise, and to test hypotheses on functional forms, parameters, and inefficiency (Coelli and Perelman, 1999; Pantzios et al., 2011). The Breusch-Pagan Lagrange multiplier (LM) was employed to test and check the presence of unobserved heterogeneity effects across households. Greene (2005a; b), the TFE and TRE models were chosen to separate time-varying technical inefficiency from unit-specific time-invariant unobserved heterogeneity. The Hausman specification test allows for checking if the true fixed effect (TFE) or true random effect (TRE) model specification is more preferred. The TRE model is more efficient, but its parameter can be biased if the Hausman test rejects the null hypothesis of no correlation between unobserved heterogeneity and the regressors and/or the model error term. The result of this test then decides the TFE estimator rather than the TRE panel estimator. Both models permit time varying-inefficiency, control for observed and unobserved heterogeneity in addition to separating inefficiency from unobserved heterogeneity. However, they differ concerning the assumption that the correlation between the unobserved heterogeneity and the regressors and/or error of the model. The TFE allows the correlation between them unlike the TRE model (Greene, 2005a, b). The test suggests that TFE is more appropriate then TRE. Therefore, the TFE model is used in the estimation.

Exogenous environmental variables $Z_{i,q}^t$ are included to account for observable factors affecting inefficiency beyond farmer's decision. These models allow α_i varying across households to control for the unobserved heterogeneity. Both the maximum likelihood estimator (MLE) of the TFE model and the TRE model can consistently estimate the unobserved effect models without dropping time-invariant variables (for example geographical variables) (Belotti et al., 2013b) though the latter drops it in the error term. Moreover, as noted by Wang and Schmidt (2002), the parameters of the technology and inefficiency are estimated using MLE in one-step to avoid biases associated with the two-step approach.

The decomposition of the residual random variable, ε_{it}, into v_{it} and u_{it} in the production function defines the stochastic production frontier, as first proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977).

Battese and Coelli (1995) assume that v_{it} are iid with mean zero and variance σ_v^2 ,i.e., v_{it} ~N (0, σ_v^2). The u_{it} are independently distributed non-negative truncations of a normally distributed random variable with mean μ_{it} and variance σ_u^2. The mean efficiency is $\mu_{it} = \alpha_i + \zeta_p Z_{iq}^t$

$\mu_{it} = \alpha_i + \zeta_p Z_{iq}^t$, where Z_{iq}^t is a vector of observed exogenous variables like household characteristics, farm characteristics and geographic-specific variables that affect efficiency, while ζ_p is a vector of unknown parameters of the inefficiency equation, and α_i

are a household-specific unobserved effect. The v_{it} and u_{it} are distributed independently of one another, and independently of the X_{it}. Two additional parameters, $\lambda = \sigma_u^2/\sigma_v^2$, and $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$, are estimated to test the significance of inefficiency in the model. This shows the proportion of the inefficiency to noise variations in the variance of the estimated model.

Data sources and collection

This study used the Ethiopia Rural Household Survey (ERHS) dataset. The ERHS is a longitudinal dataset gathered from rural Ethiopia. Addis Ababa University (AAU), the Centre for the study of Africa Economics (CSAE) at Oxford, and the International Food Policy Research Institute (IFPRI) collaboratively collected the dataset in 1994, 1999, 2004 and 2009 from 4 major regions of the country: Amhara, Oromia, Southern Nation Nationalities and Peoples (SNNP), and Tigray. These four regions of the nine administrative regions in Ethiopia account for approximately 86% of the Ethiopian population. The ERHS dataset covers many villages in rural Ethiopia, including 18 farmers' associations (FAs), 15 of the 389 woredas[2] (districts), and 1,195 households. The surveys were conducted on a sample that is stratified over the country's three major farming systems across five agro-ecological zones (AEZs) (Dercon and Hoddinott, 2004). The three main sedentary farming systems are plough-based cereal farming, mixed plough/hoe cereal farming, and *enset* (false banana) farming systems. Finally, an unbalanced panel of 4,194 observations was created over four rounds.

The northern highland AEZ 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 drought.

The central highland AEZ includes the villages of Dinki, Yetmen, and DebreBirhan, all located in the Amhara region, and Turufe Ketchema in the Oromia region.

The Arussi/Bale AEZ includes the villages of Koro Degaga and Sirbana Godeti, both located in Oromia. Adele Keke is the sole survey site locatedin the Hararghe AEZ of Oromia.

The remaining five villages of Imdibir, Aze Deboa, Gara Godo, Adado, and Doma are located in the enset-growing AEZ located in the SNNP region. Rainfall data from the National Meteorological Service Agency of Ethiopia are used.

For the variables defined above, all monetary terms are adjusted based on 1194 producer price index. The outputs of Ethiopian agriculture are crop and livestock. Crop output is represented by the value of about 60 types of crops (for example teff, maize, wheat, barley, sorghum, coffee, chat, *enset*, legumes, vegetables, etc.) which are annual and perennial crops produced in that specific production year. Livestock output is represented by the value of more than 10 types of livestock products (for example meat, live animals, hides, skins, butter, cheese, milk, chicken, eggs, dung cakes, etc.) produced in the given production year. Soil fertility is an index from one to three indicating 1 for relatively bad and 3 for the relatively fertile land.

RESULTS AND DISCUSSION

Estimation and results

All variables were normalized by their geometric mean prior to transforming them into logarithmic form (Table 1). Hence, the first order parameters of the variables can be interpreted as distance elasticities at the geometric mean[3]. The maximum likelihood estimator (MLE), as implemented in the SFPANEL module of STATA 13.1 (Belotti et al., 2013a; b), is used to estimate the parameters in Equation 6. The translog production function is one of the flexible functional forms, but it is vulnerable to multicollinearity problems, is used. To proceed with a more parsimonious specification, I conducted various specification tests. As shown by test results reported in Table 2, restrictions for constant returns-to-scale technology, Cobb-Douglas technology specification, Hicks-neutral in input, joint restriction of Hicks neutral technology, no unobserved heterogeneity, no observed heterogeneity, time-invariant technical inefficiency, and truncated normal distribution for in efficiency are rejected at the 5%. However, scale neutral technology restriction cannot be rejected at the 5% level of significance. Hence, the non-restricted model of Equation 6 is estimated. The parameter estimates of the non-restricted model and truncated-normal distribution for technical inefficiency, which are estimated simultaneously, are reported in Table 3. The consequent computations of productivity growth (Tables 4 to 6) are based on this non-restricted model specification. As shown in Table 2, there is statistically significant decay over time captured by parameter*eta*. Hence, technical efficiency has declined over time.

Parameter estimates

The estimated parametric stochastic frontier input distance function is presented. As depicted in Table 3, the input distance function parameters for inputs and outputs have the expected signs and are statistically significant at the 5% level of significance. The coefficients from the translog technology input distance function are distance elasticities at the geometric mean. The estimated input distance elasticities are 0.205, 0.003, 0.650, 0.006, 0.016 and 0.011 for labor, oxen, precipitation, seed, hoe and wealth, respectively. Modern inputs (for example seed), on average, contribute little and fertilizer does not lead to increased output. This reveals the extent to which Ethiopian agricultural production relies on conventional inputs (for example labor and precipitation) and explains why crop production in Ethiopia is sensitive to changes in the level of traditional and natural input use. The empirical evidence from the literature indicates that the probability of adopting fertilizer and improved seeds decreases as farm

[2] Woreda is a governmental administrative unit within zones of a given region, which is equivalent to the district designation elsewhere.

[3] All logged variables are divided by their geometric mean values before taking their logarithms. For the non-logged variable (that is the trend), the geometric mean value is subtracted from the observed values.

Table 1. Descriptive statistics of model variables.

Variable	Symbol	Mean	Std. Dev.	Minimum	Maximum
Output variables					
Crop product (birr)	y_1	2950.54	4115.55	1.000	45821.48
Livestock product (birr)	y_2	195.85	652.74	0.0001	14358.74
Input variable					
Farm size (hectare)	x_1	1.56	1.29	0.01	10.9
Labour (AE)	x_2	4.21	2.33	0.20	19.1
Oxen (number)	x_3	0.81	1.10	0.00	11.00
Precipitation (mm)	x_5	86.20	28.57	26.54	176.99
Seed (birr)	x_6	321.93	835.27	0.00	13400
Fertilizer (birr)	x_7	170.89	314.38	0.00	3782.37
Hoe (number)	x_8	1.26	1.55	0.00	12.00
Wealth (birr)	x_9	16506.78	39967.08	0.00	510947.90
Soil fertility (index)	x_{10}	2.36	0.66	1.00	3.00
Environmental variable					
Education (yes/no)	x_{11}	0.38	0.49	0.00	1.00
Extension(yes/no)	x_{12}	0.32	0.46	0.00	1.00
Market distance (minutes)	x_{13}	29.79	41.35	0.00	240.00
Trend t(1=1994)	t	1.46	1.09	1.00	4.00

Source: by author's computation.

Table 2. Properties of the Ethiopian Farms' Household Technology.

Restriction	Parametric Restriction	Wald test statistics	p-value
Constant returns-to-scale technology	$H_0\colon \sum_{m=1}^{M} \theta_m = -1, and \ \sum_{k=1}^{K} \phi_{mk} = \sum_{m=1}^{M} \theta_{mn} = 0$	41979.44	0.000
Cobb-Douglas technology	H_0: All interaction terms are equal to zero	4.3e+08	0.000
Hicks neutral in inputs	$H_0\colon \eta_1 = \eta_2 = \cdots = \eta_{10} = 0$	644.81	0.000
Hicks neutral in outputs	$H_0\colon \psi_1 = \psi_2 = 0$	5.23	0.073
Hicks neutral in input and output/joint significance	$H_0\colon \eta_1 = \eta_2 = \cdots = \eta_{10} = \psi_1 = \psi_2 = 0$	14050.77	0.000
No unobserved heterogeneity	$H_0\colon Var(u_{it}) = 0$	11.01	0.000
No observed heterogeneity	$H_0\colon \xi_1 = \xi_2 = \cdots = \xi_7 = 0$	84.93	0.000
Inefficiency is constant	H_0: *eta* = 0	31.86	0.000
Truncated -normal distribution for technical inefficiency	$H_0\colon \mu = 0$	3.69	0.050

Source: by author's computation.

size declines (Croppenstedt et al., 1999; Amaha, 1999; Demeke, 1999). Endale (2010) indicated that the high price of fertilizer is the major constraint for about 47.6% of the farmers followed by a supply shortage and late arrival of fertilizer. In the study period, about 49 percent of smallholder farmers use fertilizer and 39 percent according to CSA survey (CSA (Central Statistics Agency of Ethiopia) of varies years).

As shown in Table 3, the input distance elasticity for wealth, which is a proxy variable for farmers' risk preference behavior (0.011), is positive and significant at the 5% level. This shows that as farmers become wealthier or become less risk-averse, they tend to use a greater quantity of inputs and hence the input distance

Table 3. Parameter estimates of the unrestricted Translog input distance function, 1994-2009.

Variable	First-orders	$\ln x_2$	$\ln x_3$	$\ln x_5$	$\ln x_6$	$\ln x_7$	$\ln x_8$	$\ln x_9$	$\ln x_{10}$	$\ln y_1$	$\ln y_2$	t
Constant	-1.171***(0.106)											
$\ln x_2$	0.205***(0.008)	0.167***(0.009)										
$\ln x_3$	0.003*(0.002)	-0.001 (0.003)	-0.010**(0.005)									
$\ln x_5$	0.650***(0.013)	-0.126*** (0.016)	0.007***(0.002)	0.138***(0.020)								
$\ln x_6$	0.006***(0.002)	-0.000 (0.002)	-0.000 (0.000)	-0.002(0.002)	0.001**(0.001)							
$\ln x_7$	-0.001(0.001)	-0.002 (0.003)	-0.000 (0.000)	0.001 (0.002)	-0.000 (0.000)	-0.001(0.002)						
$\ln x_8$	0.016**(0.006)	-0.002 (0.001)	-0.000 (0.000)	-0.005* (0.003)	0.000 (0.000)	0.000 (0.000)	0.007*(0.004)					
$\ln x_9$	0.011*** 0.004)	-0.005 (0.009)	0.000(0.001)	0.004 (0.009)	-0.000 (0.000)	-0.000 (0.000)	0.002***(0.001)	(0.001)				
$\ln x_{10}$	-0.038(0.026)	-0.009 (0.034)	0.002(0.005)	-0.004 (0.031)	-0.000 (0.006)	0.002 (0.003)	-0.001 (0.006)	-0.001(0.003)	-0.044(0.097)			
$\ln y_1$	-0.029***(0.011)	0.003 (0.009)	-0.001(0.002)	0.005 (0.011)	-0.000 (0.000)	0.001 (0.001)	-0.000(0.001)	-0.000(0.004)	0.021(0.028)	-0.005(0.009)		
$\ln y_2$	-0.001(0.001)	-0.001 (0.002)	0.000 (0.000)	0.003***(0.001)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.001**(0.000)	-0.003 (0.002)	0.001 (0.001)	0.000(0.001)	
t	0.038***(0.005)	0.055***(0.012)	-0.002 (0.001)	-0.045*** (0.012)	0.002 (0.001)	0.002*(0.001)	0.000(0.002)	0.002(0.004)	-0.059***(0.017)			0.032**(0.012)
Inefficiency determinants -Z-variables												
x_{11}	-0.104(0.079)											
x_{12}	-0.035(0.090)											
x_{13}	0.001*(0.001)											
Sigma (u): δ_u^2	0.460***(0.014)											
Sigma(v) : δ_v^2	0.000***(0.000)											
Lambda: $\lambda = \frac{\delta_u^2}{\delta_v^2}$		5545.03*** (0.014)		Gamma:$\gamma = \frac{\delta_u^2}{\delta_u^2+\delta_v^2}$		=0.999		Log-likelihood function		=3754.74		

Significance codes: *** significant at the 1% level; **significant at the 5% level; * significant at the 10% level; robust standard errors reported in parentheses. Source: author's computations.

increases. Farmers' input allocation to each enterprise shows their risk preference behavior (Berbel, 1990). My basic premise is that farmers act rationally. Salimonu and Falusi (2007) argue that farmers' risk preference behavior affects enterprise selection, and thus input use and allocation pattern. Findings from the empirical literature suggest that absolute risk aversion decreases with wealth (Laffont, 1989; Arrow, 1965; Pratt, 1964), with income (Vickrey, 1945), and with endowment (Guiso and Paiella, 2008). The findings are in line with those of Collier and Gunning (1999), that is that farmers in developing countries tend to focus on low risk-low return activities. Since the pioneering work of Arrow (1965), who demonstrates the relationship between risk aversion and wealth, a growing body of literature has suggested individual risk attitudes are correlated with their wealth (Bucciol and Miniaci, 2011; Dohmen et al., 2011; Wik et al. 2004; Saha et al. 1994); with their constraint sets, such as access to credit, marketing, extension (Binswanger, 1980); with farm size, technology, wealth, or other personal traits (Lybbert and Just, 2007); and with fertilizer use (Holden and Westberg, 2016; McIntosh et al., 2013; Hagos and Holden, 2011).

The input distance elasticities for labor show approximately 20.5%, indicating that Ethiopian agricultural production technology is labor-intensive. This finding is not surprising given that 85% of the population depends on agriculture. As expected, the crop output elasticity (-0.029) is

Table 4. Technical efficiency and total factor productivity growth of Ethiopian Farm Households, 1994–2009.

Year	Technical efficiency	Technical efficiency change	Technical change	Scale efficiency change	Total factor productivity growth
1994	0.890	-	-	-	-
1999	0.891	0.004	0.017	0.765	0.785
2004	0.864	-0.028	0.048	-0.090	-0.070
2009	0.855	-0.015	0.080	-0.253	-0.190
Average	0.875	-0.013	0.048	0.145	0.179
Cumulative		-0.039	0.145	0.422	0.525

Source: by author's computation.

Table 5. Technical Efficiency and total factor productivity Growth of Ethiopian farm households across agro-ecological zones (AEZs).

AEZ	Technical efficiency	Efficiency change	Technical change	Scale efficiency change	Total factor productivity growth
Northern highlands	0.884	-0.009	0.045	-0.060	-0.024
Enset, hoe	0.872	0.017	0.048	0.648	0.713
Hararghe, oxen	0.853	-0.052	0.048	0.191	0.187
Arussi-Bale	0.877	-0.017	0.048	-1.084	-1.053
Central highlands	0.880	-0.036	0.048	0.193	0.205
Average	0.875	-0.013	0.048	0.145	0.179

Source: by author's computation.

Table 6. Technical Efficiency and total factor productivity growth of Ethiopian farm households across regions.

Region	Technical efficiency	Efficiency change	Technical change	Scale efficiency change	Total factor productivity growth
Tigray	0.863	-0.023	0.040	-0.293	-0.275
Amhara	0.898	-0.011	0.048	0.161	0.199
Oromia	0.857	-0.050	0.048	-0.379	-0.381
SNNP	0.871	0.017	0.048	0.648	0.713
Average	0.875	-0.013	0.048	0.145	0.179

Source: by author's computation.

negative and significantly different from zero at the 1% level. The negative value for output elasticity suggests that input distance decreases as output increases, that is the required input set to produce a given level of output decreases. The coefficient for trend variable (0.038) is positive and significant at the 1% level, indicating that the input requirement set of producing a given level of output expands if the trend variable increases. Additional factors that change over time, but that are not controlled for in the model are reflected by the trend variable.

As previously mentioned, the estimated input distance function is non-decreasing in input quantities and non-increasing in output quantities. Hence, it satisfies the monotonicity property of agricultural production technology at the point of normalization. However, as stated in Orea (2002), monotonicity with respect to the inputs of the output distance function has to be satisfied at all data points to avoid biased estimates of scale efficiency change. Likewise, the input distance function must be monotonous with respect to outputs at all data points. However, the translog function does not satisfy monotonicity globally (Orea, 2002). Hence, the estimated scale effects might be biased at those data points where monotonicity with respect to outputs is violated. In this case, I find that the percentages of violations with respect to inputs range from 0 to 45% of the observations. The violations with respect to crop product and animal products are 21 and 52% of the observations, respectively [5]. To evaluate the effect of violations concerning crop and animal outputs on scale elasticity, I calculated the average scale elasticity (returns-to-scale/RTS) for all observations, and only for those observations that satisfy monotonicity with respect to both outputs. I find that the violations concerning crop output have a negligible impact on the scale elasticity estimate. Scale effects are also the most important source of agricultural productivity growth. The average scale elasticity (returns-to-scale) is -0.14, suggesting decreasing returns to scale. On average, the producers are operating at decreasing returns to scale. Hence, the scale of production can be optimized by the reduction of input(s) to produce a given level of production. The Eigen-value decomposition of the Hessian matrix supports this finding as that the curvature properties are violated at the geometric mean. Sauer et al. (2006) argue that violations of theoretical conditions are common in flexible functional forms, partly because of the tradeoff between flexibility and theoretical consistency.

Technical efficiency

Given the estimated true fixed effects, time-varying technical efficiency scores of each farm household are obtained from the composite error term using the conditional expectation predictor of Jondrow et al. (1982). The inefficiency parameters are statistically significant with the expected signs. Again, the positive or negative signs of the parameters for these z-variables indicate that technical inefficiency has increased or decreased, respectively. Of the three z-variables controlled, the market distance measured in minutes affects inefficiency positively and significantly. The parameter estimates of gamma (γ= 0.99) in Table 3 indicates the share of technical inefficiency in the total error variance. The higher value is a measure of the suitability of the frontier approach compared with the least squares approach. Technical inefficiency accounts for approximately 99% of the total variability in output. The parameter estimates the lambda (λ= 5545.03), which measures the proportion of variance due to inefficiency as compared to statistical noise, which is many times fold than inefficiency, and it is statistically significant. The average technical efficiency score is 0.875, with a standard deviation of 0.13. This finding indicates that the average farmer produces 87.5% of the value of the output that is produced by the most efficient farmer using the same technology and inputs. This estimate is in line with the average agricultural efficiency score in China (88.4%), as reported by Yu et al. (2014) for the 1978 to 2010 period. Similar to Chinese farmers, Ethiopian farmers can improve their technical efficiency by fully utilizing existing inputs and technology. They can reduce the inputs required to produce the average output by 12.5% if their farming operation becomes technically efficient.

Agricultural productivity growth and its sources

The total factor productivity growth rates (TFP) during the study period and its decomposition into three main components are presented in Table 4. The TFP is decomposed into technical efficiency change, technical change, and scale efficiency change. The results show that overall productivity growth is positive, and both scale efficiency change and technical improvement contribute positively while technical efficiency change contributes negatively.

As shown in Table 4, the average technical efficiency score drops from approximately 89.0% in 1994 to 85.5% at the end of the study period. The temporal decline in technical efficiency can partly be explained by the household decision on how to use limited inputs like fertilizers and improved seeds, risk preference behavior of the household, fragmented and small farm size, and the learning curve related to optimally using improved technologies.

In addition, the average technical efficiency was 89.0, 89.1, 86.4 and 85.5% in 1994, 1999, 2004 and 2009, respectively. These figures indicate that households have significant room for improvement in their farming practices over these periods compared with the best performers in the agricultural sector. I report the average and cumulative productivity growth during the 1994 to 2009 period.

The productivity decomposition in Table 4 shows that the productivity increase over time is mainly driven by scale efficiency change and technical change. Moreover, my results suggest that households were somehow approaching the most productive scale size in 1999. During the study period, productivity increased by 14.5% due to scale effects and 4.8% due to technical change. However, productivity decreased by 1.3% due to technical efficiency change, which was negative except in 1999. The scale efficiency change was 76.5% in 1999; it declined to -9.0% in 2004 and -25.3% in 2009. Unexpectedly, the scale effects show the inverse relationship between farm size and agricultural productivity. The cumulative productivity growth due to scale efficiency effect and technical change was 42.2% and 14.5%, respectively positive and far greater than that due to efficiency change.

[5]The percentages of violations with respect to inputs are 0.0% for precipitation, 0.6% for farm size, 5.7% for labor, 17.6% for wealth, 23.4% for seed, 34.6 for hoe, 45.2 for ox and 51.5 % for fertilizer.

The estimates are in line with the components of average productivity growth in agriculture reported for many other developing countries. Belloumi and Salah (2009) reported similar agricultural productivity growth rates (1%) from 1970-2000 in the Middle East and North African countries (Algeria, Egypt, Iran, Iraq, Israel, Jordan, Lebanon, Libya, Mauritania, Morocco, Saudi Arabia, Sudan, Syria, Tunisia, Turkey and Yemen). Similarly, Yu et al. (2014) reported an annual agricultural productivity growth of 2% for China from 1978-2010. Moreover, Belloumi and Salah (2009) concluded that technical change is the main source of productivity growth in the Middle East and North Africa. However, Fuglie and Wang (2012) reported that long-run TFP growth was below 1% per year in sub-Saharan Africa during the 1961 to 2009 period.

However, my results are much lower than the Fulginiti and Perrin (1998) findings for Turkey, Chile, Dominican Republic, Egypt, Portugal, Malaysia and Sri Lanka, during the 1961-1985 period; technical change ranges from 92.5% (Korea) to 100.9% (Egypt) and, efficiency change ranges from 97.3% (Thailand) to 103.3% (Dominican Republic) using output-based Malmquist index and a parametric Cobb-Douglas production functions).

With reasonable confidence, I thus conclude that scale efficiency and technical improvement contributes to productivity growth more than technical efficiency improvement. This result implies that there are many opportunities to increase production through technical efficiency, technological and scale efficiency improvements.

In Table 5, the further decomposition of productivity shows that technical inefficiency is somehow different across regions and AEZs. For example, the Central and the Northern highlands, and Arrusi/Bale AEZs have higher technical efficiency and above the overall national average. The enset-growing AEZ has technical efficiency slightly below the national average. The Hararghe AEZ has the lowest technical efficiency and it is below the national average. This is because precipitation is an important factor in this rain-fed agriculture, more specifically Hararghe relatively dry region and enset-growing AEZ is a relatively wet region of the country. Technical change is almost similar across AEZs and regions except for small variation in Tigray region and Northern highlands. This suggests that farmers use similar farming technologies.

Table 6 presents regional productivity decomposition, showing that the SNNP and Amhara regions are slightly more technically efficient and above the national average; and Oromia and Tigray are slightly less efficient and below the national average. Similarly, SNNP and Amhara regions show more productivity growth than the Oromia and Tigray regions. This is because scale efficiency and efficiency change contribute to SNNP, while only scale efficiency change contributes to Amhara region.

Agricultural production is not only a function of biophysical endowments but also a result of socio-economic conditions and the policy environment, which includes the availability of labor, the demand for food, the infrastructure between farms, and the presence of input and output markets (Chamberlin and Schmidt, 2011). The negative productivity growth in 2004 and 2009 is probably linked to the following factors. First, the Eritrean-Ethiopian war in 2000 increased the average military spending to GDP ratio from approximately 2.7 to 8.5%, spending that otherwise most likely would have been used in the agricultural sector to enhance input and credit supply during this period. Second, the Ethiopian government launched the National Extension Intensification Program (NEIP) in 1995, adopting methods originally introduced by Sasakawa Global 2000 (SG2000, 1995), with the intent of enhancing the availability of inputs and access to credit. Here, we note that the reach of and funding for the NEIP was subsequently reduced, and SG2000 abandoned its extension program in 2000. Finally, argumentative and unsettled national issues, such as land ownership and economic development; the institutional and constitutional structure of the Ethiopian state; and equality of ethnic and religious communities, were brought to the forefront more specifically during and after the 2005 election that have not been yet resolved.

CONCLUSION AND POLICY IMPLICATIONS

Currently, the Ethiopian population is growing quickly, and natural resource stocks are depleting rapidly. Hence, improving agricultural productivity becomes increasingly important for several reasons: to increase agricultural production for home consumption and the market, to supply labor to other sectors, to conserve the environment, and to improve standards of living and thereby foster economic development. Future productivity growth in agriculture is also necessary to satisfy the increasing demand for food, fiber, fodder, and bio-energy, to contribute environmental conservation, and to bring Ethiopians to middle-income country in 2025.

Advances in agricultural productivity are also vital for economic development in developing countries. In developing countries with low productivity, such as Ethiopia, there is limited surplus production over and above household consumption, restricting the supply to the market. As a result, a large share of the population continues to participate in farming activities. For instance, in Ethiopia, 85% of the population farms, but these farmers cannot meet home consumption and domestic demands, mainly because of low agricultural productivity. By contrast, in the developed countries with high agricultural productivity, a greater share of the produced quantity reaches formal markets. A small share of their population engages in farming, but these farmers manage to meet their domestic and export demands because of high productivity and efficiency. Because of this, more of the labor force is available for other sectors of the economy, such as services and manufacturing, which enables the overall economy to grow faster by increased demand for products from agriculture and other sectors.

Ethiopian farmers in particular and farmers in developing countries, in general, have an objective function of input contraction. Hence, the input distance function and decomposed TFP into scale efficiency change, technological change and efficiency change was estimated using the Malmquist productivity decomposition index.

The overall average technical efficiency score has been approximately 87.5%; this indicates that an average farmer produces 87.5% of the value of the output produced by the most efficient farmer using the same technology and inputs. In other words, farm households can reduce the inputs required to produce the average output by 12.5% if their farming operation becomes technically efficient. This implies that households have significant room to improve their farming efficiency and become close to the best performers in the agricultural sector.

On average, total factor agricultural productivity growth was estimated at about 17.9% during the study period. From this, agricultural productivity growth due to scale efficiency change, technical change, and efficiency change was approximately 14.5%, 4.8%, and -1.3, respectively. The first two components were the primary annual productivity growth during this period and unlikely there was a decline in efficiency change. Notably, according to my estimates, nearly all the agricultural productivity growth in Ethiopia is due to scale efficiency and technical change. This indicates that technical efficiency improvement becomes the main sources of productivity growth in the future.

Under the current production practices, and with such small and fragmented farm size, it is critical to fulfilling home consumption, domestic market demand, and allows people to leave agriculture for other jobs. However, narrowing the gap is possible by increasing productivity via technical change, scale efficiency change, and technical efficiency change through improving training to the farmer, extension services, research and development, and agronomic practices.

Scale efficiency effect and technological improvements are important sources of productivity growth in Ethiopian agriculture. The results suggest that scale efficiency change and technical change, not technical efficiency change, have been major sources of productivity growth in Ethiopian households during the study period. The average efficiency change decreases over the study period. There are also many opportunities to increase productivity by improving technical efficiency, which implies that there are many opportunities to increase production via efficiency improvements. First, smallholder farmers are technically inefficient. Technical efficiency improvement could be enhanced by improving farmer's education, training, and extension services that could reduce mistakes and encourage developing skills. The technical change could be enhanced through improved technologies (like an improved seed, fertilizer, irrigation, tractor, combiner, amongst other technologies) that must be introduced to improve the productivity of Ethiopian agriculture. Research and extension services should generate and promote appropriate technologies to boost the productivity of agricultural production systems, including improved farm implements, high-yielding varieties, better credit systems, better fertilizer application and usage, enhanced extension services, better irrigation facilities, and improved infrastructure. It is possible to increase the scale efficiency by scaling up best agronomic practices such as fertilizer application (amount, time and rate), seed rate, weeding, ploughing and pest, and disease management. These enable the farmer to produce at a scale closer to the maximum productive scale size. To sum up, my findings suggest that scale efficiency, technological and technical efficiency improvements are the three most important areas to consider in increasing productivity growth in Ethiopian agriculture.

CONFLICT OF INTERESTS

The author has not declared any conflict of interests.

ACKNOWLEDGMENTS

The author would like to thank Addis Ababa University (AAU), the Centre for the Study of Africa Economics (CSAE) at Oxford and the International Food Policy Research Institute (IFPRI) for Ethiopia Rural Household Survey (ERHS) data, and Ethiopian National Meteorological Service Agency for rainfall data used for this article. Comments received from Eirik Romstad, Stein T. Holden and Daniel Muluwork at different stages of preparing this article are appreciated. The financial assistance received from the Norwegian State Educational Loan Fund is appreciated.

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