Food Security (2021) 13:895–912
https://doi.org/10.1007/s12571-021-01175-7

ORIGINAL PAPER

How effective is Ethiopia's agricultural growth program at improving the total factor productivity of smallholder farmers?

Hailemariam Teklewold[1]

Received: 23 January 2020 / Accepted: 23 May 2021 / Published online: 2 June 2021

Abstract
The Agricultural Growth Program (AGP) in Ethiopia is a multifaceted investment program supporting agricultural productivity and the commercialization of smallholder farmers. The AGP is expected to positively affect household food security by increasing agricultural productivity and production. The extent to which the AGP has affected farmers' economic efficiency and productivity is an interesting policy issue. This study employed a switching regression with the stochastic frontier model to investigate differences in total factor productivity (TFP) between beneficiary and non-beneficiary farmers in AGP. It also estimated the role of technological progress, technical and scale efficiencies in conditioning TFP. Results show that participation in AGP provided significantly higher TFP compared to non-participation. While technical progress did contribute to the observed increase in output, improving technical efficiency has also the potential to increase output by as much as 40% with existing technology and resources. The study suggests that there are opportunities to improve productivity growth and food security in smallholder farms over time through more active research and extension activities in Ethiopia. In the AGP, technical progress has been achieved in the use of irrigation, high yielding crop varieties, modern agricultural machinery, fertilizers, and pesticides. Since technical change is the most important source of the growth in productivity, policy changes that support the use of modern agricultural inputs directly or indirectly is likely to improve the agricultural sector in Ethiopia.

Keywords Agricultural growth program · efficiency · productivity · technical change · impact · Ethiopia

1 Introduction

In Ethiopia, the Agricultural Growth Program (AGP) is a multifaceted investment program by the government and development partners, with a focus on agricultural development. Since its inception in 2011, the AGP has implemented activities to strengthen the capacity of farmer organizations and their service providers to scale up best practices and support marketing and processing of selected agricultural outputs through engagement with the private sector. In addition, the program supported the construction, rehabilitation and management of small-scale rural infrastructure and increased the efficiency of key value chains through improved access to markets. The AGP aimed to improve agricultural productivity, enhance production efficiency and support commercialization of smallholder farmers. Growth in agricultural productivity and enhancing commercialization can increase and stabilize food supplies, and increase the ability to purchase food, with implications on household food security (Mainuddin & Kirby, 2009).

In smallholder agriculture, productivity is generally defined in terms of technical change and improvement in the efficiency with which inputs are transformed into outputs in the production process (Chambers, 1988). Technical change refers to increases in the set of production possibilities that come about through increased research and development, while technical efficiency enhancement refers to increases in output–input ratios made possible by developments in the production process (Kumbhakar & Lovell, 2000). Hence, in the context of AGP, technical progress would indicate the impact of shifts in production technology from the use of irrigation, high yielding varieties of seeds, modern agricultural machinery, fertilizers, pesticides, and other inputs. It would also capture the effects of improved utilization of land and labor resources, and changes in cropping pattern in favor of high value-added crops.

✉ Hailemariam Teklewold
hamtekbel@yahoo.com

[1] Environment and Climate Research Center, Policy Studies Institute, P.O.Box 2479, Addis Ababa, Ethiopia

There are several theoretical channels by which such types of agricultural interventions affect agricultural production and household food security (Sileshi et al., 2019; Majumder et al., 2016). Agricultural programs may: (i) impact on farmer input use decisions through changing the relative prices of agricultural inputs and outputs (Serra et al., 2005); (ii) change investment and on-farm labor supply decisions through an income effect (Young & Westcott, 2000; Serra et al., 2005); and (iii) enhance an insurance effect for possible agricultural risk mitigation (Burfisher & Hopkins, 2003). Consistent with the theoretical justification, specific benefits expected from the AGP include improved productivity, value addition and market opportunities. In these ways the program is expected to increase income, employment opportunities and the food security of smallholder households.

The income and insurance effects may shift the working motivation of farmers (such as in terms of quality and quantity of on-farm labor supply decisions), adoption of farm technologies and allocations of inputs (Zhu & Lansink, 2010). It is expected that these effects will change farmers' production capacity. The observed variation among individual farmer decisions can be associated with variations in their risk aversion behavior (Binswanger, 1980). If farmers are risk averse which is usually the case for smallholder farmers in developing countries, agricultural support policies will directly affect farm investment decisions and on farm production in the presence of uncertainty (Hennessy, 1998; Yesuf & Bluffstone, 2009).

The income effect of agricultural programs on efficiency and productivity is unknown a priori. If the agricultural program supports farmers with the required finance for technology adoption or to invest in efficiency-improving on-farm activities, then the technical efficiency level of farmers is expected to increase. On the other hand, technical efficiency may decline if farmers are less motivated to do well due to more income stemming from the program. Hence, the actual impact of the AGP on farmer performance is worth empirical investigation.

There are several studies that focus on the impacts of agricultural policy reforms on farm economic performance using efficiency and productivity analyses (e.g., Coelli et al., 2002; Hadley, 2006; Murillo et al., 2007). Furthermore, there is also extensive literature on total factor productivity (TFP) that usually decomposes TFP into the contributions of technical efficiency, technical change, and scale efficiency (Kumbhakar & Lovell, 2000; Karagiannis et al., 2004; Majumder et al., 2016). Technical change is the rise in the maximum output that can be achieved from a given level of inputs (a shift in the production frontier) while technical efficiency shift is the change in a farmer's capacity to produce maximum output given its set of production factors (how close it is to the production frontier). Scale efficiency change is the degree to which a farm household is enhancing the scale of its operations.

The objectives of this study were to evaluate the roles of technical progress, technical efficiency and scale efficiency as determinants of TFP and investigate whether farm households in AGP implementation districts were more likely to increase TFP and its components compared to those in non AGP districts. More specifically, this study examined the extent to which AGP impacts the smallholder's technological progress, farm technical and scale efficiency, and TFP.

The extent to which the AGP has affected farmers' performance in terms of change in efficiency and productivity is an interesting policy issue. Thus, by carefully examining the constituent parts of agricultural productivity and analyzing the drivers of productivity and efficiency change, this study shed light on the ways AGP can affect agricultural growth and evaluate the pathways to productivity. Furthermore, from the policy point of view, it is imperative to identify whether technological progress has stagnated over time or whether technology has been used in ways to achieve its full potential. Because technical advances and efficiency change constitute different sources of TFP growth, different policies tailored to the different parts may be required to increase household food security.

1.1 Methodological framework

1.1.1 Stochastic Frontier Analysis (SFA) and TFP components

In the case of smallholder agriculture where multiple-outputs and factors of production prevail, TFP can simply be expressed as the ratio of aggregate outputs to aggregate inputs. The general stochastic production frontier model for panel data can be written as (Battese & Coelli, 1992):

$$y_{it} = f(t, z_{it}, \beta).\exp(v_{it}).\exp(-u_{it}), \quad u_{it} \geq 0 \tag{1}$$

where y_{it} and z_{it} are respectively the vectors of outputs and production factors used in the farm in year t (t = 1,. ., T) for farm household i (i = 1, 2, 3,. .., N) where t is a time trend index that serves as a proxy for technical change; β is the vector of parameters to be estimated. The vectors v_{it} and u_{it} represent different error components that are assumed to be independently distributed. v_{it} refers to the random part of the error, while u_{it} is a downward deviation from the production frontier that can be shown by the negative sign and the restriction $u_{it} > 0$. Thus, $f(t, z_{it}, \beta).\exp(v_{it})$ represents the stochastic frontier of production and v_{it} has symmetrical distribution to capture the random effects of measuring errors and shocks that cause the position of the deterministic part of the frontier to vary from farmer to farmer. The systematic error term, u_{it}, is associated with output-orientated technical inefficiency. The level of technical efficiency (TE) in production for the i^{th} farm households at the t^{th} year, that is the ratio of observed output to potential output (which is given by the frontier), is captured by the component $\exp(-u_{it})$ (Coelli et al., 2002), and, therefore, $0 < TE_{it} < 1$.

An index of technological change (TC_{it}) for the i^{th} farm households can be directly calculated from the estimated parameters of the stochastic production frontier (Coelli et al., 2002). TC is mathematically obtained by taking the first partial derivatives of the production function with respect to the time variable, where TC < 0 is technological regression and TC > 0 indicates technological progress. Assuming a translog production technology with six inputs (see Table 2 for the description of factors of production), the model can be expressed in the following way:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{6} \beta_k \ln z_{kit} + \frac{1}{2} \sum_{k=1}^{6} \sum_{j=1}^{6} \beta_{kj} \ln z_{kit} \ln z_{jit} + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + \sum_{k=1}^{6} \beta_{tk} t \ln z_{kit} + v_{it} - u_{it} \quad (2)$$

Kumbhakar (2000) has suggested a productivity change decomposition analysis that accounts for divisions of productivity changes into technical efficiency, technical innovation and scale effects. The components of Total Factor Productivity (TFPg) can be obtained from algebraic manipulations of the deterministic part of eq. (2).

The rate of TFP change can be specified as:

$$TFP_g = TC_{it} - u + (RTS - 1) \sum_{k=1}^{6} \lambda_{zk} \cdot g_{zk}. \quad (3)$$

where RTS denotes returns to scale with $RTS = \sum_{k=1}^{6} \varepsilon_{zk}$; and $\lambda_{zk} = \varepsilon_{zk} / RTS$ is defined as shares of the k^{th} elasticity of production.

Thus, TFP can be decomposed into three elements: technical progress (TC), change in technical efficiency, denoted by $\dot{u}$ and scale efficiency (SE), given by $(RTS - 1) \sum_{k=1}^{6} \lambda_{zk} \cdot g_{zk}$.

Scale efficiency, which is traditionally considered as a measure inherently related to the returns to scale of a technology in the production process, shows how close an observed farmer is to the optimal scale (Coelli et al., 2002).

The effect of each component of TFP depends on the relative changes of each part. If technical inefficiency does not change over time, it does not have any impact on the rate of change of productivity. The same is true with technological change. However, the role of economies of scale depends both on the relative strength of technology as well as on factor intensities. The scale effect source of productivity change is present only if the production technology is characterized by the variable returns to scale (Coelli et al., 2002).

1.1.2 Estimation of impact of AGP on TFP, TC, SE and TE

We employ a regime switching regression with the stochastic frontier model to investigate change in TFP, TC, TE and SE due to AGP participation. Given that participation in the AGP is important for increasing productivity, it is intuitively reasonable to consider the econometric issue of the heterogeneity of the impacts of the program among farm households in districts where the AGP was implemented and non-AGP districts. The reduced form of the stochastic production function in eq. (2) was estimated separately for households in AGP districts and non-AGP districts. The standard econometric method of assessing the effects of program participation is to use a dummy indicator variable for the program participation over a pooled sample of observations. This assumes program participation could have only an intercept shifting effect and there are common slope coefficients for farm households in AGP and non-AGP districts. However, the set of variables that affect productivity could depend on whether one participates in the program or not. If this is true, then estimation of eq. (2) on a sample of farm households that pools across the program participation classification may lead to biased estimates. I used the Chow test (Chow, 1960), which rejected the hypothesis of equality of the slope coefficients for the two groups [$\chi^2(35) = 116.49$ with p value = 0.000]. This result confirmed that controlling for input factors and time variable, farm productivity is structurally different between farm households in AGP and non-AGP districts.

The gaps between AGP and non-AGP participant in TE, SE, TC and TFP may be decomposed into a part accounted for by differences in household heterogeneities and a part accounted for by differences in coefficients. The former is interpreted as AGP participation differences in TE, SE, TC and TFP attributable to differences in underlying socioeconomic characteristics between households in AGP and non-AGP districts.

Consider the following exogenous switching regression model specified by regressing the household specific indices of TE, TC, SE and TFP against a set of farm and household specific characteristics for the group $AGP = 0, 1$ (non-participant and participant, respectively):

$$\begin{array}{ll} I_{it,1} = \alpha_{0,1} + \alpha_{t,1} t + \alpha_1 x_{it,1} + c_{i,1} + \varepsilon_{it,1} & \text{if AGP} = 1 \\ I_{it,0} = \alpha_{0,0} + \alpha_{t,0} + \alpha_0 x_{it,0} + c_{i.o} + \varepsilon_{it,0} & \text{if AGP} = 0 \end{array} \quad (4)$$

where I_{it} is the TE, SE, TC and TFP index, x_{it} is a column vector of covariates hypothesized to be correlated with efficiency and factor productivity; α is unknown parameters to be estimated. The time trend variable t captures temporal changes in efficiency and factor productivity; c_i is unobserved individual specific random disturbance which is constant over time; ε_{it} is an idiosyncratic error term which varies across time and individuals and is independently and normally distributed with mean zero and common variance σ^2.

Because all the dependent variables are censored (they are limited between 0 and 1), the parameters for TFP, TC, TE and SE are obtained through maximum likelihood estimation (MLE) by applying a two-tailed correlated random effects (CRE) Tobit procedure or the Mundlak–Chamberlain device, following Mundlak (1978) and Chamberlain (1984). The Tobit approach has been used in several studies to evaluate the factors influencing farm inefficiencies and technology adoption (e.g., Fernandez-Cornejo, 1994; Wadud, 2003). To implement the CRE framework in eq. (4), I included a vector of variables containing the means for household i of all time-varying covariates. These variables have the same value for each household in every year but vary across households. One benefit of the CRE estimator is that the assumption of independence between the covariates and unobserved individual specific random term can be relaxed by including the vector of time-averaged variables. This can control for time-constant unobserved heterogeneity as with fixed-effects while avoiding the problem of incidental parameters in nonlinear models and allows for measurement of the effects of time-constant independent variables (Wooldridge, 2002).

The conditional expectations for each outcome variable were computed by manipulating model (4) in the actual and counterfactual scenarios:

$$E(I_1|AGP=1) = \delta_1 t + \alpha_1 x_1 \tag{5a}$$

$$E(I_0|AGP=1) = \delta_0 t + \alpha_0 x_1 \tag{5b}$$

$$E(I_0|AGP=0) = \delta_0 t + \alpha_0 x_0 \tag{5c}$$

$$E(I_1|AGP=0) = \delta_1 t + \alpha_1 x_0 \tag{5d}$$

The "actual" AGP and Non-AGP scenarios are the ones actually observed in the data (5a and 5c, respectively). The "counterfactual" scenarios show what the TE, SE, TC and TFP outcomes for households in AGP districts (AGP = 1) would be, if they had had the same characteristics as the households in non-AGP districts, and vice versa (5b and 5d). Alternatively, what the TE, SE, TC and TFP outcomes of households in non-AGP districts (AGP = 0) would be if the responses (coefficients) to their characteristics had been the same as the current returns to the characteristics of households in the AGP districts, and vice versa. Using these conditional expectations and considering the AGP participation variable as a "treatment" variable, the average TE, SE, TC and TFP expected values in the real and hypothetical scenarios are presented in Table 1 and their definitions are given below the table[1]:

The AGP participation gap in TE, SE, TC and TFP for households in the AGP districts is defined if households in the AGP districts had had the same characteristics as they do now, but the same returns to those characteristics as households in the non-AGP districts have now. This is given as the difference between (5a) and (5b):

$$\begin{aligned} ATT_I &= E(I_1|AGP=1) - E(I_0|AGP=1) \\ &= (\delta_0 t + \alpha_0 x_1) = (\delta_1 - \delta_0)t + (\alpha_1 - \alpha_0)x_1 \end{aligned} \tag{6}$$

Similarly, the expected change in TE, SE, TC and TFP for households in the non-AGP districts if they had had the same returns to their characteristics as the households in the AGP districts have now, is given as the difference between (5c) and (5d):

$$\begin{aligned} ATU_I &= E(I_1|AGP=0) - E(I_0|AGP=0) \\ &= (\delta_1 t + \alpha_1 x_0) - (\delta_0 t + \alpha_0 x_0) \\ &= (\delta_1 - \delta_0)t(\alpha_1 - \alpha_0)x_0 \end{aligned} \tag{7}$$

Equations (6) and (7) are equivalent to the average treatment effect on the treated (ATT) and on the untreated (ATU), respectively. In this study, the ATT and ATU indicate what the TE, SE, TC and TFP outcomes that households in the AGP districts would have had if the factors facing them had been the same as those currently facing households in the Non-AGP districts, and vice versa. The difference between (6) and (7) can also be used to compute the composition or heterogeneity effects, for instance, due to resource quality difference, managerial skill, and differential access to services. The composition (heterogeneity) effects show, respectively, what the difference would have been if all households had had the current AGP households' responses and the current non-AGP households' responses to the observable characteristics. This provides information on whether the AGP participation gap on TE/TFP is larger or smaller due to characteristics of AGP households or non-AGP households. Households in the AGP and non-AGP districts do in fact have different observable characteristics, and this would have an impact even if their responses to the characteristics had been the same.

1.2 The AGP program, data and study areas

The AGP aims primarily to increase agricultural productivity and market access for key crop and livestock products in targeted areas with increased participation of women and youth. The program has the following components (Berhane et al., 2013). The first aims to sustainably increase the productivity of crop and livestock value chains, improve access to markets, and enhance agricultural commercialization. Crop production and productivity improvement is targeted through measures such as scaling up of best practices, promoting use of fertilizers, increasing the availability and adoption of improved inputs, agronomic practices, and increased use of

[1] I suppress the t and i notations from the equations for ease of presentation.

Table 1 Conditional expectations, Agricultural Growth program (AGP) effects and heterogeneity effects

AGP sample	AGP participation		Program effects
	AGP-participation	AGP-non participation	
AGP-participants	(5a) $E(I_{itAGP=1}\|AGP=1)$	(5b) $E(I_{itAGP=0}\|AGP=1)$	$_{AIT}$= (5a) – (5b)
AGP-non participants	(5c) $E(I_{itAGP=1}\|AGP=0)$	(5d) $E(I_{itAGP=0}\|AGP=0)$	$_{ATU}$= (5c) – 5d)
Heterogeneity effect (HE)	$HE_{AGP=1}$=(5a)−(5c)	$HE_{AGP=0}$=(5b)−(5d)	

Note: (5a) and (5d) denote observed expected TE, SE, TC or TFP; (5b) and (5c) denote counterfactual expected TE, SE, TC or TFP; AGP=1 if AGP participants; AGP=0 if AGP-non participants; $I_{it,\ AGP=1}$ TE, SE, TC or TFP for farmers in the AGP-Districts; $I_{it,\ AGP=0}$ TE, SE, TC or TFP for farmers in the non-AGP Districts; ATT (average treatment effects for the treated) and ATU (Average treatment effects for the untreated) represent the average AGP program effects for the AGP participants and AGP non-participants, respectively;$HE_{AGP=1}$ and $HE_{AGP=0}$ denote heterogeneity effect (or difference caused by difference in characteristics) for AGP participants and non-participants, respectively; Program effects is the difference caused by difference in response to program participation.

small-scale irrigation. In the livestock sub-sector, increased growth is expected to be achieved through improving availability of feed both in quantity and quality, provision of veterinary services, improved breeds and market infrastructure, and enhancing value addition. The second component aims to finance and provide technical support for rural infrastructure. Priority was given to water development for small-scale irrigation. The expected results from this component are improved small-scale irrigation infrastructure to increase productivity and enhance the adaptive capacity of farmers to extreme climatic shocks, market infrastructure for enhanced commercialization, and capacity of public institutions for enhanced service delivery.

The models developed in the previous sections were applied to three rounds of panel datasets spanning a 5-year period, 2011–2017. The data used for this study was obtained from a farm household survey in AGP participant and non-AGP districts. A total of 93 districts, out of which 61 AGP participant and 32 non-AGP districts were selected from the four regional states of the country, Amhara, Tigray, Oromia and SNNP. A randomly selected 7927 farm households participated in the baseline survey. The attrition rate for the whole period was about 10%.

The household survey collected agriculture-specific production data, household characteristics and community features. As a first step, I distinguished the main factors of production considered in the stochastic frontier model: land, labor, seed, animal power, fertilizer and agrochemicals. Land was defined as the total hectares of land cultivated by the household, and labor input was the sum of family and hired labor time measured in adult equivalent person-days. Animal power was the number of oxen owned by the household which was used as a proxy for animal traction power. Farmers produce different crop types on different plots. But for the purpose of this study, I aggregated crop output and included all seasons. This variable was measured in monetary value ('000 Birr/ha). The current district level average price was used to aggregate the values of the crops. The summary statistics for inputs and output variables for the entire sample and disaggregated by year and AGP participation status are presented in Table 2. Similarly, Table 2 provides the definitions and descriptive statistics of the prospective explanatory variables. The selection of the empirical specification is grounded on a theoretical behavioral hypothesis and draws on previous similar empirical technical efficiency and total factor productivity literature (Huang & Kalirajan, 1997; Coelli et al., 2002; Wadud, 2003; Zhu & Lansink, 2010; Majumder et al., 2016; Sileshi et al., 2019).

Based on these empirical works and economic theory, household, farm, and location characteristics were summarized in the empirical specifications. These include household composition, education, wealth (including livestock ownership) and other sources of income such as participation in off-farm activities; social capital and network (membership in formal and informal organizations), current shocks/stresses experienced on crop production (such as plot level disturbances and rainfall shocks), land tenure security, and agro-ecology of the location. A wide range of plot-specific attributes such as soil fertility, depth, slope, farm size in hectares, farm fragmentation, distance of plot from residence and detailed agricultural practices were also considered in the empirical specification.

2 Empirical results

2.1 Hypothesis tests

I estimated the pooled frontier model for the crop farms with AGP participation as a dummy variable and examined whether AGP participation status specific frontier function was a better representation than the pooled frontier production function. The Chow test result ($\chi^2(35) = 116.49$ with p value

Table 2 Descriptive statistics and variable description

Variable	Description	AGP-non participation						AGP-participation						Total	
		2011		2014		2017		2011		2014		2017			
		Average	SD	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD
Farm input and output															
Rc	Farm revenue ('000 Birr/ha)	23.75	32.75	25.63	14.65	26.28	33.52	20.69	30.69	25.17	96.98	26.43	51.93	23.75	32.75
Fa	Farm size, hectare	2.16	2.30	1.65	4.13	1.75	1.78	2.16	2.07	2.06	5.92	1.68	1.48	2.16	2.30
La	Labor (person days/ha)	208.40	267.81	192.90	666.06	224.08	175.29	198.33	358.92	149.55	578.81	230.78	184.93	208.40	267.81
Fe	Fertilizer, kg/ha	60.44	99.95	89.12	216.58	134.82	122.22	62.60	116.59	98.75	239.71	184.97	266.82	60.44	99.95
Se	Seed, kg/ha	80.97	42.72	91.97	36.68	89.40	24.04	72.02	39.13	89.13	37.08	88.28	23.79	80.97	42.72
Ox	Number of oxen	1.83	2.37	2.40	17.12	3.67	105.31	1.98	2.42	2.16	16.17	1.90	67.53	1.83	2.37
Ag	Agro-chemical, lit./hectare	0.35	5.28	1.24	30.10	1.74	20.54	2.71	80.26	1.33	21.41	2.00	15.00	0.35	5.28
Household characteristics															
Agehead	Age of the head, years	43.31	15.36	45.77	15.68	47.60	15.94	42.57	14.81	44.17	15.11	45.90	15.45	43.31	15.36
Genderhead	1=if male headed household	0.72	–	0.67	–	0.70	–	0.71	–	0.71	–	0.71	–	0.72	–
Education	Education, years	4.11	6.45	2.86	5.10	3.05	5.27	2.92	5.44	3.20	5.52	2.99	5.26	4.11	6.45
HHsize	Family size	4.85	2.15	4.77	2.05	4.61	2.07	4.75	2.10	4.78	2.14	4.72	2.16	4.85	2.15
Social capital and extension															
Member	Number of groups of membership	2.55	2.51	2.54	2.14	2.92	2.35	2.51	2.21	2.62	2.26	2.72	2.31	2.55	2.51
Connections	1=if hold a position in the group	0.15	–	0.21	–	0.24	–	0.14	–	0.22	–	0.21	–	0.15	–
Extension	1=if contact extension service	0.36	–	0.48	–	0.40	–	0.32	–	0.41	–	0.34	–	0.36	–
Wealth															
TLU	Tropical livestock unit	5.97	5.87	5.62	5.96	4.20	4.59	6.36	6.42	5.50	6.14	4.28	4.95	5.97	5.87
Credit	1=if credit is needed but unavailable	0.71	–	0.70	–	0.65	–	0.63	–	0.63	–	0.64	–	0.71	–
Offfarm	1=if participates in off-farm	0.10	–	0.14	–	0.11	–	0.10	–	0.14	–	0.12	–	0.10	–
Shocks															
Plotshock	Plot level shocks index, 1=worst	0.10	0.11	0.04	0.10	0.10	0.10	0.10	0.11	0.05	0.09	0.09	0.10	0.10	0.11
Rainshock	Rainfall shocks index, 1=best	0.58	0.34	0.48	0.44	0.85	0.23	0.60	0.35	0.49	0.44	0.83	0.26	0.58	0.34
Farm characteristics															
Plotdistance	Average plot distance, minutes	19.38	64.73	13.81	20.60	22.99	48.33	17.40	28.13	18.78	40.97	20.91	32.44	19.38	64.73
Fragment	Number of parcels	3.65	1.78	3.33	1.94	3.86	2.18	3.44	1.71	3.08	1.78	3.81	2.16	3.65	1.78
Lemarea	High fertile area, hectare	0.16	0.25	0.15	0.30	0.12	0.25	0.21	0.26	0.21	0.66	0.14	0.22	0.16	0.25
Lemtefarea	Medium fertile area, hectare	0.09	0.17	0.07	0.46	0.13	0.19	0.09	0.18	0.10	0.54	0.09	0.18	0.09	0.17
Flatarea	Flat slope area, hectare	0.16	0.25	0.15	0.27	0.21	0.32	0.21	0.26	0.24	0.77	0.19	0.27	0.16	0.25
Midsloparea	Medium slope area, hectare	0.09	0.18	0.09	0.47	0.02	0.07	0.10	0.19	0.09	0.41	0.03	0.08	0.09	0.18
Maize	Maize area, hectare	0.32	0.88	0.36	2.92	0.22	0.37	0.33	0.93	0.38	4.35	0.20	0.42	0.32	0.88

Table 2 (continued)

Variable	Description	AGP-non participation						AGP-participation						Total	
		2011		2014		2017		2011		2014		2017			
		Average	SD	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD
Permanent	Permanent crop area, hectare	0.55	1.41	0.36	3.31	0.40	0.87	0.56	1.31	0.68	6.73	0.36	0.76	0.55	1.41
Vegetable	Vegetable crop area, hectare	0.10	0.46	0.03	0.36	0.09	0.48	0.11	0.38	0.09	1.46	0.08	0.31	0.10	0.46
Belg	Area share for short rain crop production	0.02	0.06	0.04	0.17	0.03	0.07	0.02	0.07	0.04	0.16	0.02	0.07	0.02	0.06
Tenure security															
Tenure	Own farm area, ha	1.70	3.42	1.49	3.55	1.69	3.01	1.86	3.24	1.95	8.17	1.66	2.44	1.70	3.42
Register	Share of plots registered	0.77	0.40	0.91	0.21	0.83	0.33	0.73	0.42	0.89	0.24	0.86	0.29	0.77	0.40
Conflict	1 = if involved in border conflict	0.24	–	0.15	–	0.15	–	0.27	–	0.13	–	0.15	–	0.24	–
Agricultural practices															
Irrigation	1 = if use irrigation	0.08	–	0.06	–	0.07	–	0.07	–	0.08	–	0.11	–	0.08	–
Manure	Share of plots covered with manure	0.60	0.49	0.42	1.03	0.37	0.48	0.55	0.50	0.29	0.88	0.33	0.47	0.60	0.49
Compost	Share of plots covered with compost	0.10	0.25	0.09	0.28	0.07	0.21	0.09	0.23	0.04	0.19	0.05	0.17	0.10	0.25
Improvseed	Share of improved seeds	0.31	0.64	0.41	0.49	0.53	0.44	0.25	0.56	0.41	0.49	0.49	0.46	0.31	0.64
Recycleseed	Share of recycled improved seeds	0.67	1.10	0.63	0.48	0.39	0.49	0.80	0.86	0.62	0.48	0.44	0.50	0.67	1.10
Rowplanting	1 = if use row planting	0.44	–	0.50	–	0.45	–	0.47	–	0.49	–	0.43	–	0.44	–
Diversification	Number of crops grown	6.97	3.65	4.87	4.34	4.87	2.59	6.52	3.45	4.64	4.29	4.66	2.70	6.97	3.65
Agro-ecology															
Dega	1 = if Dega (Highland)	0.20	–	0.16	–	0.31	–	0.20	–	0.21	–	0.15	–	0.20	–
Weynadega	1 = if Weyna-dega (Midland)	0.54	–	0.51	–	0.44	–	0.44	–	0.47	–	0.50	–	0.54	–
Number of observations		**2296**		2296		2296		4803		4803		4803		7099	

<0.0000) suggested that the production technology specification for AGP participant and non-participant are structurally different and hence the hypothesis that the pooled frontier function is a correct presentation of AGP participant and non-participants' production technology was rejected. Therefore, the subsequent presentation will be based on the estimation of the results separately for the AGP participant and non-participant specific production frontier function.

I conducted a formal specification test to determine the chosen model specification fitting to the data. The first null hypothesis that the Cobb–Douglas production function is a good representation for the data ($H_0 : \beta_{kj} = 0, k, j = 1, \ldots, 6$) was strongly rejected indicating that the Translog production function is the preferred model.[2] The second null hypothesis, that there is no technological change over time ($H_0 : \beta_t = \beta_{tt} = \beta_{tj} = 0, j = 1, \ldots, 6$) was also strongly rejected by the data, indicating that technological change exists in the study area.[3] The magnitude and direction of technological change will be determined and discussed later.

The result provides statistical confirmation that the distribution of the random variable, u_{it}, has a non-zero mean and is truncated below zero. The null hypothesis $\eta = 0$ which suggests time invariant technical inefficiency model, was statistically rejected in both AGP participants and non-participants' models. This showed that technical efficiency levels vary significantly over time. η equals 0.135 and 0.052 in the AGP participant and non-participant models respectively, showing that the technical inefficiency of crop production increased by 14% for participants and 5% for non-participants in the period 2011 to 2017. The test of significance in both AGP participant and non-participant models indicated the rejection of the null hypotheses of no technical inefficiency effects.

2.2 Econometric estimates – Stochastic Frontier model

Here I provide results of the parameter estimates of the stochastic production functions and technical efficiency, technological change, returns to scale and their roles to the observed change in productivity. The parameter estimates for the Translog stochastic frontier production function are shown in Table 3. Out of 35 coefficients, 21 coefficients from the AGP-districts and 16 from the non AGP-districts estimations were significantly different from zero at least at the 10% level indicating the importance of some of the interactions and non-linearity among variables. All the five inputs considered in the estimations were found to be the major determinants of output growth in multiple ways: in isolation or when interacted with the other inputs, or both. These factors of production, however, have shown heterogeneous effects on output growth for farm households in the AGP and non-AGP districts. This result confirms the presence of structural differences of production functions among households with and without AGP.

The indicator for returns to scale was obtained by summing the elasticities of the five factors of production included in the model. Table 4 indicates that the average farm household in the AGP districts had decreasing returns to scale (0.604) and so did the average households in the non-AGP districts (0.227). The null hypothesis of constant returns to scale was statistically rejected at 1% significance level in favor of decreasing returns in both AGP and non-AGP districts. Overall, the result suggests that an increase in the amounts of productive factors leads to a less than proportionate output growth; and the scale elasticity for farm households in AGP districts was statistically lower than households in the AGP districts. This means that even if the scale effect on productivity change could be high in both AGP and non-AGP farm households, relative output change is higher for farm households in non-AGP districts than households in the AGP districts.

Table 3 also shows that there is significant technological bias for both groups of households. The negative and significant coefficient of the time-trend variable in the model indicates that there was an initial technological regress on production; however, it increased over time as indicated by the significant positive coefficients of the squared terms. The frontier is shifting downwards at a rate of 16% for households in the AGP districts and 11% for households in the non-AGP districts. However, the non-linearity of technical change implies that there was technological progress over time that moved the production frontier upwards. Technological progress for farm households in the AGP districts is about 10%. This was statistically higher than the technical progress for households in the non-AGP districts, by about 2%. Moreover, based on a joint significance test of inputs, the null hypothesis of neutral technological progress[4] ($H_0 : \beta_{tj} = 0, j = 1, \ldots, 6$ inputs) was generally rejected at a 1% significance level. The next section examines whether the changes in productivity are caused mainly by changes in the scale of production, or by differences in rates of technological change or technical efficiency change.

2.3 TFP and its decomposition

Table 5 presents the average TFP scores and corresponding decomposition results by year and based on AGP participation status. The TFP index is decomposed into technical change (TC), technical efficiency change (TE) and scale efficiency

[2] $\chi^2(20) = 85.58$ with $p < 0.001$ for households in the AGP districts and $\chi^2(21) = 57.71$ with $p < 0.001$ for households in the non-AGP districts.

[3] $\chi^2(8) = 567.00$ with $p < 0.001$ for households in the AGP districts and $\chi^2(8) = 219.38$ with $p < 0.001$ for households in the non-AGP districts.

[4] $X^2(6) = 155.82$ with $p < 0.001$ for households in the AGP districts and $X^2(6) = 96.88$ with $p < 0.001$ for households in the non-AGP districts.

Table 3 Stochastic production functions estimations for crop productions in AGP and Non-AGP districts (Dependent variable: Farm revenue)

Variables	All samples		AGP-participation		AGP-non participation	
	Coefficient.	Standard Error	Coefficient.	Standard Error	Coefficient.	Standard Error
Ln (Fa)	−0.099	0.276	0.135	0.345	−0.650	0.469
Ln (La)	0.209*	0.134	0.183	0.164	0.306	0.234
Ln (Fe)	0.688***	0.143	0.516***	0.176	0.991***	0.250
Ln (Se)	2.923***	1.121	3.402***	1.381	2.478	1.948
Ln (Ox)	1.789***	0.507	1.169**	0.600	3.247***	0.974
Ln (Ag)	0.155	0.426	0.840*	0.524	−1.003	0.740
Ln $(Fa)^2$	−0.044***	0.012	−0.055***	0.015	−0.020	0.020
Ln $(La)^2$	−0.016*	0.010	−0.031***	0.012	0.012	0.017
Ln $(Fe)^2$	−0.040***	0.011	−0.032***	0.013	−0.057***	0.019
Ln $(Se)^2$	−0.087	0.127	−0.136	0.157	−0.030	0.219
Ln $(Ox)^2$	−0.094***	0.034	−0.076*	0.044	−0.105**	0.055
Ln $(Ag)^2$	0.002	0.019	−0.008	0.024	0.023	0.031
Ln (La) Ln (Fa)	−0.018*	0.011	−0.005	0.014	−0.038**	0.019
Ln (La) Ln (Ox)	0.011	0.024	0.041	0.031	−0.039	0.041
Ln (La) Ln (Ag)	−0.054***	0.016	−0.055***	0.019	−0.043*	0.028
Ln (La) Ln (Fe)	−0.010**	0.005	−0.010*	0.006	−0.012	0.009
Ln (La) Ln (Se)	0.055**	0.029	0.066**	0.036	0.024	0.050
Ln (Fa) Ln (Ox)	−0.138***	0.050	−0.170***	0.061	−0.159*	0.093
Ln (Fa) Ln (Ag)	0.015	0.026	−0.003	0.036	0.029	0.040
Ln (Fa) Ln (Fe)	−0.033***	0.012	−0.013	0.015	−0.057***	0.021
Ln (Fa) Ln (Se)	0.128**	0.064	0.031	0.080	0.338***	0.109
Ln (Ox) Ln (Ag)	0.043	0.062	−0.024	0.079	0.160	0.109
Ln (Ox) Ln (Fe)	−0.011	0.022	−0.035	0.026	0.036	0.038
Ln (Ox) Ln (Se)	−0.207**	0.114	−0.131	0.135	−0.428**	0.215
Ln (Ag) Ln (Fe)	−0.016	0.015	−0.029*	0.018	0.012	0.027
Ln (Ag) Ln (Se)	−0.057	0.095	−0.190*	0.117	0.144	0.164
Ln (Fe) Ln (Se)	−0.031	0.030	−0.022	0.037	−0.038	0.053
Ln (Time)	−14.284***	0.961	−15.938***	1.218	−10.925***	1.671
Ln $(Time)^2$	7.379***	0.315	7.873***	0.383	6.473***	0.529
Ln (Fa) X Ln (Time)	0.264***	0.062	0.353***	0.078	0.087	0.105
Ln (La) X Ln (Time)	−0.170***	0.037	−0.136***	0.047	−0.244***	0.063
Ln (Fe) X Ln (Time)	−0.101***	0.025	−0.049*	0.031	−0.212***	0.044
Ln (Se) X Ln (Time)	−1.163***	0.138	−1.213***	0.171	−1.159***	0.238
Ln (Ox) X Ln (Time)	−0.144	0.104	−0.051	0.127	−0.314*	0.180
Ln (Ag) X Ln (Time)	0.216***	0.061	0.269***	0.076	0.132	0.104
AGP_Districts (1=if yes)	−0.262***	0.065				
Constant	5.346**	2.579	5.240*	3.188	3.847	4.513
Diagnostic statistics						
Ln σ^2	3.034***	0.165	3.669***	0.207	2.990***	0.089
Inverse Logit γ	−2.247	1.816	0.129	1.735	−2.235***	0.916
u	−2.661**	1.878	−3.980**	1.672	−1.219	4.659
η	0.069***	0.023	0.135**	0.071	0.052***	0.029
$\sigma2$	20.291	3.546	39.19	4.24	20.519	3.332
γ	0.096	0.157	0.532	0.181	0.108	0.144
σ_u^2	1.939	3.525	20.86	4..206	2.211	3.308
σ_v^2	18.256	0.218	18.33	0.263	18.306	0.383
Wald $\chi^2(37)$	5560***		3834***		1665***	

Table 3 (continued)

Variables	All samples		AGP-participation		AGP-non participation	
	Coefficient.	Standard Error	Coefficient.	Standard Error	Coefficient.	Standard Error
Joint significance of Agro-ecology variables, χ^{2}23)	19.11***		9.84***		9.76***	

Note: *, ** and *** indicate statistical significance at 10, 5 and 1% level

(SE). Overall, there are substantial variations in the growth parameters and their components across years and across households in AGP and non-AGP districts. There was substantial variation in average technical efficiencies over time among households in AGP and non-AGP districts.

This result also shows a consistent decline in the technical efficiency of farmers over time from 68% in 2011 to 57% in 2017 for farm households in AGP districts; and from 70% in 2011 to 68% in 2017 for households in non-AGP districts (Table 5). While technical efficiency of farm households was decreasing over time in both AGP and non-AGP districts, the average annual rate of decrease for households in AGP districts (4%) was statistically higher than for households in non-AGP districts (1%). This implies that farmers in AGP districts have become more technically inefficient over time during the AGP implementation period.

Scale efficiency in this study was small across years and for households in both AGP and non-AGP districts. Table 5 shows that the average scale efficiencies were 20% for farmers in the AGP districts and 25% in non-AGP districts. This implies that these farmers could have further increased their farm output by 75 to 80% if they had adopted an optimal scale of operation. The results also show that about 39% of farm households in the non-AGP districts and 49% of those in the AGP districts showed increasing returns to scale (Table 4). These farmers produce at a suboptimal level, i.e., the output levels of these groups of farmers were lower than the optimal levels and they should expand their operation to reach the optimal scale. The scale efficiency of these farmers is noticeably lower than the average 20% (about 10–12% for both groups of households) and the average returns to scale was higher than unity (1.7–2.6). Only about 4 % of the farmers in the sample were characterized as operating at an optimal scale, while 47% of the AGP and 57% of the non-AGP groups had decreasing returns to scale.

Table 6 presents the average results of the TFP decomposition for farm households in AGP and non-AGP groups. In aggregate, TFP increased at an average rate of 7.8% per annum during the AGP implementation period (2011–2017). This growth rate was slightly higher for farm households in AGP districts than households in non-AGP Districts (8.3% versus 6.6%). The rate of change in TFP for farm households in both AGP and non-AGP districts appeared to be relatively heterogeneous over the two sub periods (2011 to 2013 and 2013 to 2017) of the AGP implementation period. In the AGP districts, annual growth of TFP was positive but decreasing gradually — increasing by about 14% during 2011–2013 and by about 3 % during 2013–2017. Similarly, the annual growth of TFP for farm households in non-AGP districts showed a

Table 4 Estimated Scale Elasticity and Scale Efficiency

	AGP- participants				AGP-non participants			
	Observation (%)	Scale Elasticity	Scale Efficiency	Technical Efficiency	Observation (%)	Scale Elasticity	Scale Efficiency	Technical Efficiency
Total sample (mean)	100	0.604[a,b] (2.264)	0.253 (0.346)	0.569 (0.181)	100	0.247 a,b (1.497)	0.204 (0.328)	0.675 (0.541)
• Supra-optimal scale	47.12	−1.458 (1.283)	0.390 (0.403)	0.634 (0.122)	56.91	−0.799 (1.114)	0.275 (0.372)	0.662 (0.061)
• Optimal scale	4.00	1.000 (0.040)	0.119 (0.043)	0.571 (0.179)	4.38	1.000 (0.039)	0.036 (0.072)	0.683 (0.064)
• Sub-optimal scale	48.89	2.557 (0.985)	0.132 (0.233)	0.634 (0.203)	38.72	1.695 (0.438)	0.120 (0.239)	0.693 (0.062)

Note: Numbers in parenthesis are standard deviation; 'a' indicates scale elasticity of farm households in both AGP and non-AGP participant districts are statistically different from one (constant returns to scale), with 95% confidence interval of [0.567–0.641] for AGP participants and [0.212–0.282] for AGP-non participants; 'b' indicates scale elasticity for farm households in AGP-non participants are statistically lower than scale elasticity of households in AGP-participants at $p < 0.0001$

Table 5 Summary statistics of Total Factor Productivity (TFP), Technical Change (TC), Technical Efficiency (TE) and Scale Efficiency (SE) index by time and AGP participation status

Sample	Item	Year			Average
		2011	2014	2017	
All	TFP	0.674 (0.315)	1.036 (0.402)	1.143 (0.385)	0.951 (0.421)
	TC	−0.127 (0.019)	0.193 (0.079)	0.279 (0.075)	0.115 (0.186)
	SE	0.122 (0.255)	0.263 (0.351)	0.327 (0.373)	0.237 (0.341)
	TE	0.679 (0.186)	0.58 2(0.168)	0.536 (0.115)	0.599 (0.169)
AGP participants	TFP	0.664 (0.339)	1.085 (0.367)	1.165 (0.405)	0.974 (0.431)
	TC	−0.136 (0.009)	0.247 (0.009)	0.331 (0.006)	0.149 (0.203)
	SE	0.123 (0.264)	0.281 (0.103)	0.354 (0.392)	0.253 (0.347)
	TE	0.678 (0.213)	0.554 (0.161)	0.480 (0.087)	0.569 (0.181)
AGP-non participants	TFP	0.706 (0.243)	0.995 (0.396)	1.097 (0.333)	0.930 (0.386)
	TC	−0.111 (0.012)	0.089 (0.010)	0.172 (0.007)	0.048 (0.119)
	SE	0.120 (0.237)	0.226 (0.391)	0.271 (0.731)	0.204 (0.328)
	TE	0.695 (0.062)	0.675 (0.061)	0.655 (0.059)	0.675 (0.063)

declining trend over the two sub periods from 9.5% during the first sub period to 3.8% during 2013–2017.

The substantial share of TFP growth is related to technical progress (increasing at an average annual rate of 6.8%) and increases in scale efficiency (3.4% of annual growth). In both groups of farm households, the contribution of technological change for increasing factor productivity appeared to be positive over the two sub-periods of the AGP implementation period, although the change in technological progress over the two periods was not constant for farm households in the AGP districts (12.8 and 2.8%) and households in the non-AGP districts (it varied from 6.7 and 2.8).

Table 6 Decomposition of total factor productivity (TFP) annual change, 2011–2017

Sample	Item	Annual change		
		2011–2014	2014–2017	2011–2017
All	TFP	1.1213	1.0347	1.0780
	TC	1.1067	1.0287	1.0677
	SE	1.0470	1.0213	1.0342
	TE	0.9677	0.9847	0.9762
AGP-participants	TFP	1.1390	1.0277	1.0833
	TC	1.1277	1.0280	1.0778
	SE	1.0527	1.0243	1.0385
	TE	0.9587	0.9753	0.9670
AGP-non participants	TFP	1.0953	1.0377	1.0665
	TC	1.0667	1.0277	1.0472
	SE	1.0353	1.0167	1.0260
	TE	0.9933	0.9933	0.9933

Technical change contributed about 88% of the increase in productivity between 2011 and 2014, and 83% between 2014 and 2017. While scale efficiency showed a positive annual growth rate of about 3 % (but with a declining trend over time from 5% to 2%), its contribution to the growth of TFP also increased between the two sub periods from 39% to 42%. In contrast, the technical efficiency had a diminishing growth rate over time in both groups of households. However, the rate of decline of technical efficiency was low and constant over time (1% annually) for farm households in non-AGP districts compared with households in the AGP districts, (it declined annually from 3% to 5%). This technical inefficiency contributed to a decline of TFP growth rate by about 5% annually.

Figure 1 also shows the effect of TC, SE and TE on TFP more clearly. The relationship between TFP and TE was not linear for both groups of farm households. TFP declines at lower levels of TE. The positive contribution of TE to the growth of TFP was observed at higher levels of TE. However, as described above, Fig. 1 (Panel b) also shows an almost linear relationship between TC and TFP. Similar to the pattern of TE and TFP, Fig. 1 (Panel c) shows a U-shaped relationship between SE and TFP. Compared to 'Panel a' of Fig. 1 (the effect of TE on TFP), the positive contribution of SE on TFP starts at an early stage of SE, before the farm household attains about 50% scale efficiency.

2.4 Impacts of AGP on TE, SE, TC and TFP

The findings on TE, SE, TC and TFP so far is based on simple averages of the outcomes among farm households in AGP and non-AGP districts. However, this approach does not disentangle whether the change in TE, SE, TC and TFP is due to program effects or other households and farm heterogeneities.

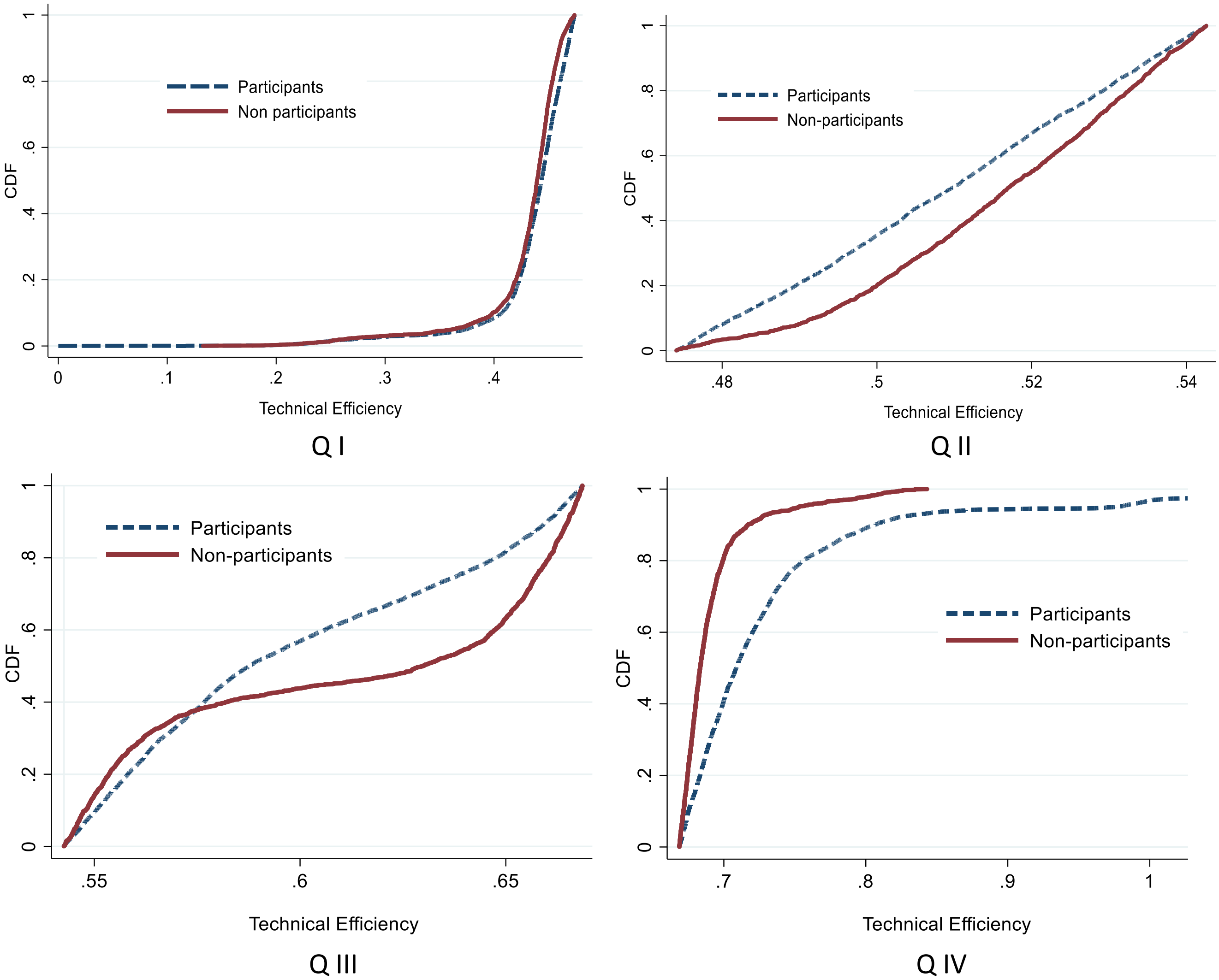

Fig. 1 Cumulative distribution for impact of AGP participation on technical efficiency (TE) by quantiles of TE

Accordingly, as described above, I estimated the CRE regression of TE, SE, TC and TFP indices for households separately in the AGP participant districts and non-AGP districts. The estimation results of the outcomes (TE, SE, TC and TFP) equations will be discussed in the next section. However, several variables in the model showed significant correlation with the outcome variables and there were differences between the outcome equations coefficients among households in AGP and non-AGP districts. This illustrates the heterogeneity in the sample with respect to TE, SE, TC and TFP.

From the regression estimates, the average AGP effect on the population (ATE) was derived, as well as the average AGP effect on the AGP participant (ATT) and the average treatment effect on the non-participants (ATU). The unconditional average effect is presented in Table 7. The unconditional average effects indicate that the average annual TE, SE, TC and TFP indices for farm households in the AGP districts were significantly different from those of farm households in the non-AGP districts. This presents an 11%, 15% and 32% TFP, TC and SE increment, respectively, and a 16% decline in TE due to AGP. This expected effect is different from the percentage difference in the simple sample means between farm households in the AGP and non-AGP districts shown in Table 5. The simple contrast with unconditional average effect among participant and non-participant groups may provide misleading conclusions because the approach does not take in to consideration the difference in the outcome variables that may be caused by observed and unobserved factors.

The result of the decomposition analysis for the switching regression with CREs model for TFP, TC, TE and SE are presented in Tables 8, 9, 10 and 11. As in Teklewold et al. (2013), I analyzed the differences in TFP, TC, TE and SE among AGP participant and non-participant households into two parts: the first part is attributable to differences in underlying socio-economic characteristics (such as household and farm characteristics) called "composition or heterogeneity effect", while the second is attributable to the "response" to

Table 7 Unconditional AGP participation effects on total factor productivity, technological progress, technical efficiency and scale efficiency (results from correlated random effects estimation)

Sample	AGP participation		Program effects (C)
	AGP- participants, (A)	AGP-non participants (B)	
Total Factor Productivity	0.836 (0.001)	0.704 (0.107)	0.131 (0.002)***
Technological Progress	0.148 (0.001)	0.052 (0.001)	0.096 (0.002)***
Technical Efficiency	0.567 (0.001)	0.678 (0.0004)	−0.110 (0.001)***
Scale Efficiency	0.347 (0.002)	0.262 (0.001)	0.085 (0.002)***

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level

these characteristics called "program effects". To determine the average effects of the program on the participants, the expected outcome variables (TFP, TC, TE and SE) for AGP participant were compared with their counterfactual - what they would have been if they had not participated in AGP - by comparing columns A and B of Tables 8, 9, 10 and 11. This is shown in column C computed as the difference between columns A and B.

Participation in AGP lead to a 13% higher TFP (i.e., 0.848 to 0.716); on average, compared to non-participation (Table 8). The difference was statistically significant. In the counterfactual cases, farm households who actually participated in AGP would have generated less TFP if they did not participate (see first row of column B in Table 8). Similarly, farm households that did not participate would generate 13% more TFP (i.e., 0.811 to 0.682) if they did participate (see second row of column A in Table 8) than if they did not participate in the program. Generally, under both conditions, TFP was higher for AGP participant farm households than non-participant households.

The result from the transitional heterogeneity gaps indicates that TFP of AGP participants and non-participants increased by 3.7% (i.e., 0.848 to 0.811) and 3.4% (i.e., 0.716 to 0.682), respectively, if TFP is conditioned by AGP participant characteristics than AGP non-participant characteristics. The program effects alone do not explain the overall difference in TFP status between farm households in AGP and non-AGP districts. In this case, while both AGP participation and non-participation would show an improvement in TFP status from using the AGP participant resources and characteristics, the benefit for non-participants is larger compared to the participants; the increase in TFP is higher for the former by 0.4%.

Table 9 presents the contribution of AGP on TC. Participation in AGP significantly contributed to household level TC. Both the ATT (average AGP effect of TC on the participant) and ATU (average AGP effect of TC on the non-participant) shows that AGP participation leads to a higher TC, on average, compared to non-participation. Under both conditions, the difference was statistically significant. Farm households who actually participated in AGP would have generated less TC if they did not participate (see first row of column B in Table 9).

The results from the transitional heterogeneity gaps indicate heterogeneity of TC due to a composition effect. Thus, AGP participation and non-participation increased TC by 0.4% (i.e., from 0.149 to 0.145) and 1.6% (i.e., from 0.054 to 0.048), respectively, if TC was conditioned by AGP participants' characteristics than characteristics of non-participants. The program effect does not alone give the overall AGP difference in TC between farm households in AGP and those in non-AGP districts. Similar to other components of TFP, the negative heterogeneity effects indicate that while AGP participation and non-participation would show an improvement in TC status from using the resources of AGP participants and

Table 8 Average expected total factor productivity (TFP) and conditional AGP participation effects (results from correlated random effects estimation)

Sample	AGP participation		Program effects (C)
	AGP-participation, (A)	AGP-non participation (B)	
AGP-participants	0.848 (0.001)	0.716 (0.001)	0.133 (0.002)***
AGP-non participants	0.811 (0.002)	0.682 (0.002)	0.129 (0.003)***
Heterogeneity effects	0.037 (0.003)***	0.034 (0.002)***	0.004 (0.001)**

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level

Table 9 Average expected technical progress (TC) and conditional AGP participation effects (results from correlated random effects estimation)

Sample	AGP participation		Program effects (C)
	AGP-participation, (A)	AGP-non participation (B)	
AGP-participants	0.149 (0.002)	0.054 (0.001)	0.095 (0.002)***
AGP-non participants	0.145 (0.002)	0.048 (0.001)	0.098 (0.003)***
Heterogeneity effects	0.004 (0.003)	0.016 (0.002)***	−0.003 (0.001)**

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level

characteristics of households, non-participants benefit more compared to the participants.

I also estimated AGP differences in TE (Table 10). In general, the result provides further evidence on AGP difference in TE status due to program effects and due to the overall composition effect (differences in observed socio-economic characteristics). The average AGP gap in TE status of AGP participation compared to non-participation conditional on characteristics of AGP participants represents a 10% decline in TE (from 0.680 in AGP participation to 0.577 in non-participation). Similar to this, the AGP gap conditional on characteristics of non-participants showed a decline in TE of AGP participation by about 12% compared to non-participation (0.546 versus 0.669). There were also significant transitional heterogeneity effects. The TE status would decrease by about 3 % (i.e., from 0.577 to 0.546) and increase by 1 % (i.e., from 0.680 to 0.669) respectively for AGP participation and non-participation, if the respective TE was conditioned by the resources and characteristics of AGP participants rather than those of non-participants. Thus, AGP participation and non-participation show an improvement in TE status from using resources and characteristics of the participants. Participants in AGP benefit more from TE compared to non-participants due to the program.

Results on the average causal effect of AGP on SE are in Table 11. The results reveal that the SE differential is also apparently caused by differences in household and farm characteristics. AGP non-participants could have been more scale efficient had they had the resources and characteristics of AGP participants. The results also indicate that there were some sources of heterogeneity due to program effects that makes AGP participation more scale efficient than non-participation under both AGP participants' and non-participants' characteristics. Column A of row 1 and column B of row 2 in Table 11 shows that the SE of non-participant households is lower (0.343 versus 0.253), on average, than the AGP participant households. However, with the counterfactual condition (column A of second row) where the non-participants have AGP participants' response coefficients, the difference will be reduced to about −1% (0.343 versus 0.354).

Column C presents the treatment effects of AGP on SE. Non-participation results in lower SE. With the counterfactual conditions (column of B of row 1) that the AGP farm households had the non-AGP households' characteristics and returns, the SE would still be 8 % lower. Similarly, in the counterfactual case that the AGP non-participant households had the characteristics of AGP households, the mean SE will be 10% less than what it is now.

Finally, I examined the evolution of TE and TFP across households in AGP and non-AGP districts by quantiles of the TE and TFP distributions to see the patterns of distributions between AGP and non-AGP households at the extreme values. Figure 2 shows the cumulative distributions for the effect of AGP participation on TE by quantiles of TE. The result indicates that in the fourth quartile (i.e., the upper tails of the TE distribution) the cumulative distribution of TE for farm

Table 10 Average expected technical efficiency (TE) and conditional AGP participation effects (results from correlated random effects estimation)

Sample	AGP participation		Program effects (C)
	AGP-participation, (A)	AGP-non participation (B)	
AGP-participants	0.577 (0.001)	0.681 (0.001)	−0.104 (0.001)***
AGP-non participants	0.546 (0.001)	0.669 (0.001)	−0.123 (0.001)***
Heterogeneity effects	0.031 (0.002)***	0.011 (0.001)***	0.019 (0.002)***

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level

Table 11 Average expected scale efficiency (SE) and conditional AGP participation effects (results from correlated random effects estimation)

Sample	AGP participation		Program effects (C)
	AGP-participation, (A)	AGP-non participation (B)	
AGP-participants	0.343 (0.002)	0.266 (0.002)	0.077 (0.003)***
AGP-non participants	0.354 (0.003)	0.253 (0.002)	0.102 (0.004)***
Heterogeneity effects	−0.011 (0.004)**	0.013 (0.003)***	−0.025 (0.005)***

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level

households in the AGP districts dominates that of farm households in the non-AGP districts. This is shown by the cumulative distribution functions (CDF) of TE of farm household in the AGP districts being constantly below that of households in the non-AGP districts (Fig. 2, Panel d). In the middle part (the second and third quantiles) of TE distributions, the cumulative distribution of TE for farm households in the non-AGP districts dominated that of farm households in the AGP districts (Fig. 2, Panel b and Panel c). The result may suggest that although participation in AGP has a role in improving the efficiency and productivity level of farm households, there is a limited contribution of AGP in lifting those farm households who are found at the lower tail of efficiency and productivity distribution.

3 Discussions

The results indicate that most of the production inputs used in the AGP in Ethiopia had positive first-degree coefficients and

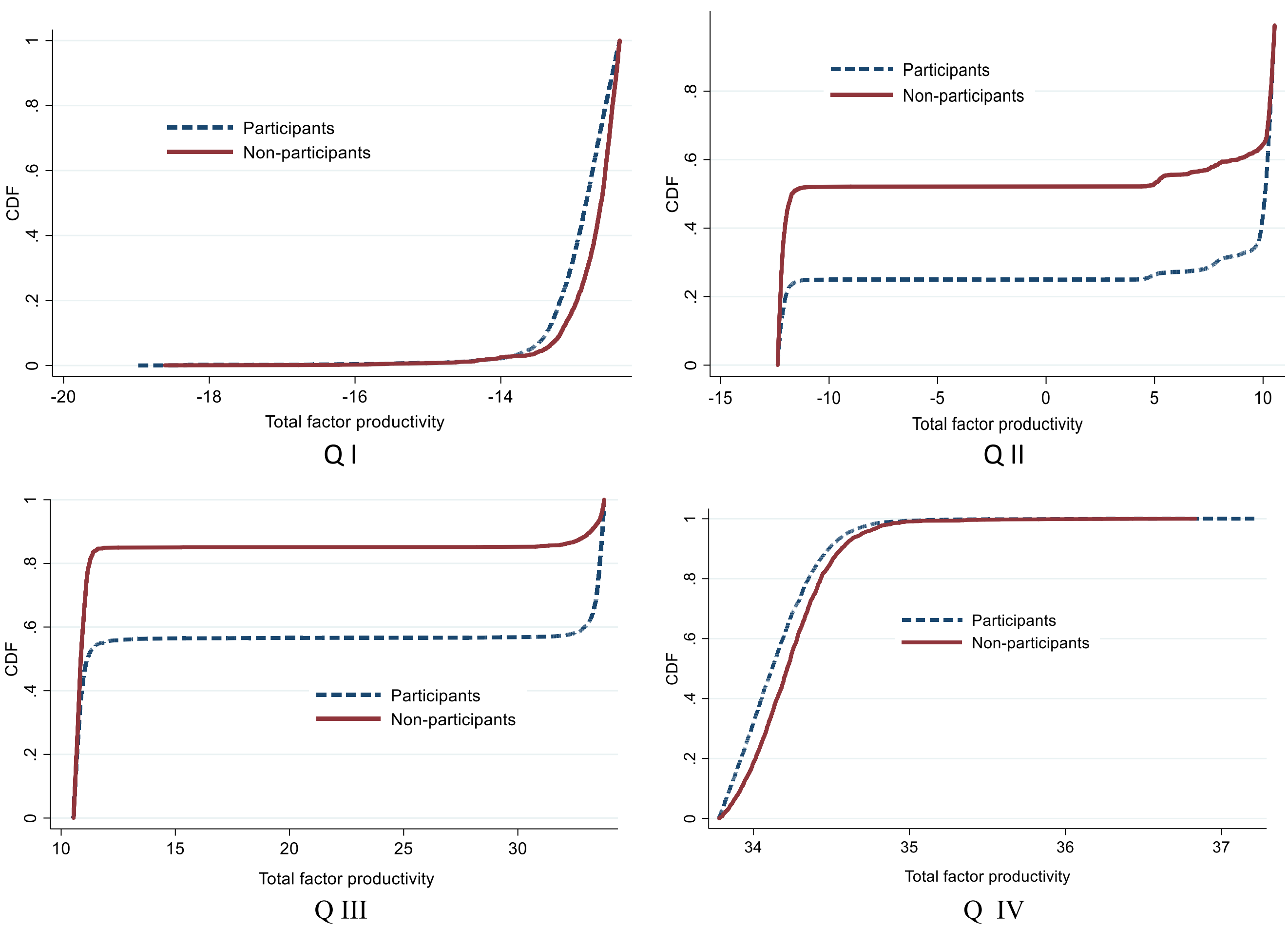

Fig. 2 Cumulative distribution for impact of AGP participation on total factor productivity by quantiles of Total Factor Productivity (TFP)

negative quadratic terms. This suggests that the impacts of the different factors of production on agricultural output growth were heterogeneous. For instance, keeping all other inputs constant, a 1% increase of fertilizer usage would result in a 0.5–1% increase in output, but with diminishing returns. The non-linear effect of fertilizer as well as its significant interaction with other inputs suggested that use of fertilizer has a positive output elasticity for farm households in the AGP districts and negative elasticity in the non-AGP districts. For AGP districts, the highest output elasticity is due to the complementarity of multiple farm inputs. The result was consistent with earlier studies on the use of multiple farm inputs for higher output elasticity (Villano et al. (2015).

The findings also suggest that land remains the most important factor of production for all farm households with an output elasticity of 1.5 for participants in the AGP and 1.0 for non-AGP participants. The high elasticity of land area is not surprising because in the presence of small size farms, as in Ethiopia, this factor can be considered a quasi-fixed input (Alvarez & Arias, 2004; Madau, 2007). The direct effect of labor had a positive output elasticity between 0.18–0.31, but that result was not statistically significant. However, with an increase in labor, labor has statistically significant negative output elasticity at −0.03 for farm households in the AGP districts.

Technical change normally involves the contraction/expansion of inputs and outputs and changes the marginal rates of technical substitution among the inputs (Coelli et al., 2002). The interaction terms of technology and farm inputs in the model capture the neutral and non-neutral technical change component of the total factor productivity change. Technological progress was associated with labor supply, fertilizer use and seed saving in both AGP and non-AGP districts. Moreover, while technological progress involved use of land and agro-chemicals in AGP districts, it was neutral to these inputs in non-AGP districts. The results also reveal no technological progress in the use of animal power in AGP districts, but animal power saving in non-AGP districts. The finding suggests greater scope of technological progress through AGP and the effective use of farm inputs.

On average, farmers in the AGP and non-AGP districts are respectively 57 and 68% efficient in using technologies. The average technical efficiency estimates from this study are comparable with technical efficiency of smallholder farmers recorded by some previous studies such as Wondimu (2016) and Abrar and Morrissey (2006) who reported 57–61% technical efficiencies for Ethiopia. Technical efficiency improvement refers to increases in output–input ratios made possible by improvement in the production process with the existing technology and resources (Kumbhakar, 2000; Coelli et al., 2002). The result generally suggests that improving technical efficiency such as through technical advice and extension services has the potential to increase output by about 32% for farmers in the non-AGP districts and 43% for farmers in the AGP districts.

The declining trend of technical efficiency over time in this study suggests that farm households in both AGP and non-AGP districts have a slow rate of output growth. This supports the assertion that farmer technical inefficiency is one of the most important elements affecting factor productivity in smallholder farming (Kumbhakar, 2000; Wadud, 2003). On the other hand, the results suggest that scale inefficiency is obtained mainly because the farms operate at a suboptimal scale, with increasing returns to scale. Wondemu (2016) suggests that lack of a competitive land market may be the primary factor that prevents farmers from fully exploiting economies of scale in Ethiopia and suggested further land consolidation as one potential source of productivity growth.

The significant positive growth rate of TFP in this study implies that technical progress has compensated for the minimal contribution of scale efficiency and the negative contribution of technical inefficiency to TFP growth in Ethiopia. The reason for the technological progress may be the favorable investment effect from the AGP through measures such as providing finance and technical support to scale up of best practices, increasing the availability and adoption of improved inputs (seeds and fertilizers), agronomic practices, and increased use of small-scale irrigation (Berhane et al., 2013). Thus, farm households in AGP districts benefit from increasing factor productivity relative to farm households in districts not included in the program That is, findings in this study support the notion that the AGP may influence agricultural productivity by encouraging investment on land and adoption of new technologies (Hadley, 2006; Villano et al., 2015).

4 Conclusions and policy implications

This study assessed the technical and scale efficiency, technical progress and total factor productivity growth in smallholder crop agriculture in Ethiopia using a stochastic frontier approach. The effects of the agricultural growth program and household and farm characteristics on total factor productivity and its components were evaluated. The econometric results confirmed that households in the AGP districts, on average, had an increased total factor productivity and technical change, but a decreased technical efficiency compared with households in non-AGP districts. This difference can be partly explained by the differences in observable endowments; the switching regression treatment effects established a significant difference between ATT and ATU, showing significant heterogeneity effects. This indicates that although the AGP program resulted in a positive effect on total factor productivity, technical change and scale efficiency, there were important additional sources of total factor productivity, technical change and scale efficiency changes due to differences in observed characteristics.

There are important policy implications from the analysis in this study. It is evident from the analysis that the critical factor affecting total factor productivity is the rate of technological progress. Thus, any policy change which affects the use of modern agricultural inputs directly or indirectly would have a role in the growth of agriculture in Ethiopia. While research and development are important in determining the country's agricultural production potential and increasing household food security status, some issues need to be taken care of. In the long run, the growth in output must rely on improvements in technical efficiency. But, the principal difficulty in the 5-year period covered by the Agricultural Growth Program lies in the slow or negative rate of increase in technical and scale efficiency. This indicates that there is a growing urgency for sustained improvements in technical advice and extension services, which requires a more active role for the public sector in research and extension activities in collaboration with farmers to bring inefficient farmers closer to the frontier over time. Emphasis should be on the communication of research results to farmers in usable forms and the establishment of regional and national means to enhance research-extension-farmer linkages and the efficiency and relevance of technology generation and transfer. In addition, as indicated by the locational variability in efficiency, the potential for efficiency improvements in different locations is substantial.

Compliance with ethical standards

Conflict of interest The author declares no conflict of interest.

References

Abrar, S., & Morrissey, O. (2006). Supply response in Ethiopia: Accounting for technical inefficiency. *Agricultural Economics, 35*, 303–317.

Alvarez, A., & Arias, C. (2004). Technical efficiency and farm size: A conditional analysis. *Agricultural Economics, 30*, 241–250.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis, 3*, 153–169.

Berhane, G., Dereje, M., Hoddinott, J., Koru, B., Nisrane, F., Tadesse, F., Taffesse, A.S., Worku, I. & Yohannes, Y. (2013). Agricultural Growth Program (AGP) of Ethiopia — Baseline Report 2011. Ethiopia strategy support program II (ESSP II) international food policy research institute (IFPRI). Addis Ababa. Ethiopia.

Binswanger, H. (1980). Attitude towards risk: Experimental measurement in rural India. *American Journal of Agricultural Economics, 62*, 395–407.

Burfisher, M.E., & Hopkins, J.W. (2003). Decoupled payments: Household income transfers in contemporary U.S. agriculture. USDA-ERS agricultural economic report no. 822 (USDA, Washington, DC, 2003).

Chamberlain, G. (1984). Chapter 22 Panel data. *Handbook of Econometrics, 2*, 1247–1318.

Chambers, R. G. (1988). *Applied production analysis: A dual approach*. Cambridge University Press.

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica, 26*, 591–605.

Coelli, T., Rahman, S., & Thirtle, C. (2002). Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: A non-parametric approach. *Journal of Agricultural Economics, 53*, 607–626.

Fernandez-Cornejo, J. (1994). Non-radial technical efficiency and chemical input use in agriculture. *Agricultural and Resource Economics Review, 23*, 11–21.

Hadley, D. (2006). Patterns in technical efficiency and technical change at the farm-level in England and Wales, 1982–2002. *Journal of Agricultural Economics, 57*, 81–100.

Hennessy, D. A. (1998). The production effects of agricultural income support policies under uncertainty. *American Journal of Agricultural Economics, 80*, 46–57.

Huang, Y., & Kalirajan, K. P. (1997). Potential of China's grain production: Evidence from the household data. *Agricultural Economics, 17*, 191–199.

Karagiannis, G., Midmore, P., & Tzouvelekas, V. (2004). Parametric decomposition of output growth using a stochastic input distance function. *American Journal of Agricultural Economics, 86*, 1044–1057.

Kumbhakar, S. C. (2000). Estimation and decomposition of productivity change when production is not efficient. *Econometric Reviews, 19*, 425–460.

Kumbhakar, S. C., & Lovell, C. (2000). *Stochastic frontier analysis*. Cambridge University Press.

Madau, F. A. (2007). Technical efficiency in organic and conventional farming: Evidence from Italian cereal farms. *Agricultural Economics Review, 8*, 5–21.

Mainuddin, M., & Kirby, M. (2009). Agricultural productivity in the lower Mekong Basin: Trends and future prospects for food security. *Food Security, 1*, 71–82.

Majumder, S., Bala, B. K., Mohamed, F. A., Haque, M. A., & Hossain, M. A. (2016). Food security through increasing technical efficiency and reducing postharvest losses of rice production systems in Bangladesh. *Food Security, 8*(2), 361–374.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica, 64*, 69–85.

Murillo, C., Santander, C., & Sperlich, S. (2007). An empirical assessment of the EU agricultural policy based on firm level data. *Journal of Economics and Statistics, 227*, 273–294.

Serra, T., Goodwin, B. K., & Featherstone, A. M. (2005). Agricultural policy reform and off-farm labour decisions. *Journal of Agricultural Economics, 56*, 271–285.

Sileshi, M., Kadigi, R., Mutabazi, K., & Sieber, S. (2019). Impact of soil and water conservation practices on household vulnerability to food insecurity in eastern Ethiopia: Endogenous switching regression and propensity score matching approach. *Food Security, 11*(4), 797–815.

Villano, R., Bravo-Ureta, B., Solıs, D., & Fleming, E. (2015). Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps. *Journal of Agricultural Economics, 66*, 129–154.

Wadud, M. A. (2003). Technical, allocative and economic efficiency of farms in Bangladesh: A stochastic frontier and DEA approach. *The Journal of Developing Areas, 37*, 109–126.

Wondemu, K.A. (2016). Decomposing sources of productivity change in small-scale farming in Ethiopia, working paper series N° ***237*** African development Bank, Abidjan, Côte d'Ivoire.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. MA. USA. MIT Press.

Yesuf, M., & Bluffstone, R. A. (2009). Poverty, risk aversion and path dependence in low-income countries: Experimental evidence from Ethiopia. *American Journal of Agricultural Economics, 91*, 1022–1037.

Young, C. E., & Westcott, P. C. (2000). How decoupled is U.S. agricultural support for major crops? *American Journal of Agricultural Economics, 82*, 762–767.

Zhu, X., & Lansink, A. O. (2010). Impact of CAP subsidies on technical efficiency of crop farms in Germany, the Netherlands and Sweden. *Journal of Agricultural Economics, 61*, 545–564.

Hailemariam Teklewold is a Research Fellow at the Environmental and Climate Research Center for Ethiopia, Policy Studies Institute. He has a PhD in Economics from the Department of Economics, University of Gothenburg, Sweden; and MSc and BSc degree both from the Department of Economics, Addis Ababa University. He is an agricultural economist where his research focuses on the economics of sustainable agricultural technologies, climate smart agricultural interventions, and analyzing the determinants of adoption of multiple sustainable and climate smart agricultural practices and their impacts on household welfare, labor demand, production risk, and environment in some African countries.