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Analysis of levels and determinants of technical efficiency of wheat producing farmers in Ethiopia

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Wheat is one of the most important cereal crops in Ethiopia, ranking fourth in total cereals production (16%) next to maize, sorghum and teff. Despite its potential for wheat grain production, Ethiopia falls short of being self-sufficient in wheat, and is currently a net importer of wheat grain. This study examines levels of and determinants of technical efficiency of wheat producing farmers in Ethiopia. Data was collected from 2017 farm households from the four major wheat growing regions of Ethiopia where around 85% of the country wheat production comes from. Cobb-Douglas functional model were used to analyze level of technical efficiency whereas quantile regression (QR) technique were employed to analyze factors that affect technical efficiency. The study indicated the average efficiency level of wheat producing farmers is 0.66 implying the huge potential to increase wheat production given the existing technological level and without any additional investment in agricultural research. Several institutional, socioeconomic and biophysical and agro ecological factors affect technical efficiency in wheat production in Ethiopia.

Key words: Technical efficiency, wheat, Ethiopia.

INTRODUCTION

Agricultural research and development, in general, contributes to agricultural growth and total factor productivity by increasing crop and livestock yields through development of new technologies and increased technological diffusion and adoption (Nicostrato and Mark, 2015). Therefore, investment in agricultural research is one of the key priority area of governments in developing countries that aimed at improving production and productivity of agriculture which play crucial role in the development of the entire economy.

Transformation of the agriculture sector will be central in Ethiopia's drive to reach middle-income country status by 2025 (ATA, 2014). But the transformation process could be hampered by many challenges which includes limited farmers access to information on technologies, limited access to inputs and financial services, poor market access, among others. These bottle necks are identified as key impediments for improving productivity of major crops such as wheat, maize and tef that have strategic importance to transform the country's economy and

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contribute to the overall socioeconomic transformation of smallholder farmers in the country (ibid).

Wheat is one of the strategic crops that is given due emphasis both in the country's GTP-I and GTP-II as well as in the agricultural transformation agenda of the country. Increasing its production and productivity has been key strategic goal of research and extension institutions in the country. Despite several efforts that have been made to achieve self-sufficiency in wheat, the country is still importing large volume of wheat every year (FAO STAT, 2014).

In an effort to achieve higher growth, several yield enhancing technologies have been generated and disseminated to farm households, but production of wheat continued to face inefficiencies which posed serious challenge to improve the country's ability to fulfill the ever growing demand for wheat. This calls for the need for investigating factors that are the very causes of inefficiencies in wheat production system so that appropriate policy measures that address the causes could be designed and implemented. For making sound and appropriate policy measures information that represent the entire wheat growing areas of the country should be made available. Previous studies conducted by Shumet, (2012), Solomon (2014), Mesay et al. (2013) and Kaleab (2011) conducted to analyze technical efficiency lack country-wide representativeness as they were based on data collected only from very few woredas1. This study, however, have used data collected from seven major agro-ecological areas of the four biggest regional states in Ethiopia (Oromia, Amhara, Tigray and SNNP) which are known for their high wheat production potential where more than 85% of the country wheat production is obtained from. Therefore, nationally representative information on technical efficiency of wheat production is produced which provide reliable information for national level program design and policy response for the entire wheat production system in Ethiopia.

This study, therefore, analyzes technical efficiency of wheat production in major wheat growing areas of Oromia, Amhara, Tigray and SNNP. The study employed a stochastic production frontier technique for investigating technical efficiency of smallholder farmers that are using improved technologies. This study has also investigated household, social, economic and institutional factors that affected technical efficiency of wheat producing farmers in the major wheat growing areas of the country.

CONCEPTUAL AND ANALYTICAL FRAMEWORK

Kopmans (1951) and Shephard (1953) were regarded as pioneers in developing theoretical literature on production efficiency, in the early 1950s. Koopmans (1951) provided a definition of technical efficiency as a producer is technically efficient if it is n longer possible to produce any further output without producing less of some other output or using more of some input. Ferguson (1996) defined production function as a function that relates maximum possible output using a given amount of combination of inputs.

Measuring efficiency empirically was started by Farrell (1957) which later inspired Koopmans et al. (1951) to develop and define ways of measuring cost efficiency, followed by the development of techniques of decomposing cost efficiency into technical and allocative efficiencies. The production technology of a farm is represented by a stochastic production function specified as:

$$Y_i = f(X_i;\beta)\exp(v_i - u_i) \quad (1)$$

Y_i denotes output for firm, i, X is the vector of inputs used in the production process, by i^{th} firm, β is a vector of parameters to be estimated, $f(X_i;\beta)$ is a true representation of a farm production function, u_i is non-negative random variable associated with technical inefficiency, assumed to be independently and identically distributed, $N(0,\sigma_u^2)$ and truncated at Zero, of the normal distribution with mean μ and variance $\sigma_u^2(|N(0,\sigma_u^2)|)$. v_i represent the stochastic error term. The maximum likelihood estimates yield β, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$. Following Jondrow et al. (1982), the technical efficiency estimation is given by the mean of the conditional distribution of inefficiency term μi given ε; and thus defined by:

$$E\left(\frac{u_i}{\varepsilon_i}\right) = \sigma^2\left[\frac{f(\frac{\varepsilon_i\lambda}{\sigma})}{1-F(\frac{\varepsilon_j\lambda}{\sigma})} - \frac{\varepsilon_i\lambda}{\sigma}\right] \quad (2)$$

Where f and F represent the standard normal density and cumulative distribution functions, respectively, and:

$$\lambda = \frac{\sigma_u}{\sigma_v} \quad (3)$$

where ${\sigma_v}^2$ and ${\sigma_u}^2$ are variance of the stochastic model and the inefficiency model, respectively. Equations 1 and 2 provides estimate of u and v after replacing ε, σ and λ by their estimate.

Quantile regression for analyzing determinants of technical efficiency

Standard linear regression techniques summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function

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[1]Woreda is the lower administrative unit which is equivalent to district. A woreda consists of several kebeles which are the lowest administrative units in the government structure of Ethiopia.

$\mathrm{E(y|x)}$. As a result, it fails to provide a more comprehensive picture of the effect of the predictors on the response variable.

For a distribution function $F_Y(y)$ one can determine for a given value of y the probability τ of occurrence. Now quantiles do exactly the opposite. That is, one wants to determine for a given probability τ of the sample data set the corresponding value y. In ordinary least square (OLS), one has the primary goal of determining the conditional mean of random variable Y, given some explanatory variable x_i, $\mathrm{E}[Y|x_i]$. Quantile regression (QR) goes beyond this and enables us to pose such a question at any quantile of the conditional distribution function. It focuses on the interrelationship between a dependent variable and its explanatory variables for a given quantile. Quantile regression overcomes thereby various problems that OLS is confronted with. Frequently, error terms are not constant across a distribution, thereby violating the axiom of homoscedasticity. Also, by focusing on the mean as a measure of location, information about the tails of a distribution are lost. And last but not least, OLS is sensitive to extreme outliers, which can distort the results significantly.

In this study, in analyzing determinants of technical efficiency, we will use quantile regression technique in order to reveal the overall picture of the relationship between the dependent variable an socioeconomic and institutional variables that affect efficiency. Quantile regression essentially transforms a conditional distribution function into a conditional quantile function by slicing it into segments. These segments describe the cumulative distribution of a conditional dependent variable Y given the explanatory variable x_i with the use of quantiles. For a dependent variable Y given the explanatory variable $X = x$ and fixed, $0 < \tau < 1$, the conditional quantile function is defined as the $\tau - th\ quantile$ $Q_{Y|X}(\tau|x)$ of the conditional distribution function $F_{Y|X}(y|x)$. In quantile regression, as opposed to OLS, the minimization is done for each subsection where the estimate of the quantile function is achieved with the parametric function. Consider the standard linear model in a population, with intercept α and $K\ x\ 1$ slopes β:

$$Y = \alpha + X\beta + u$$

Assume $E(u^2) < \infty$, so that the distribution of u is not too spread out. Given a large random sample, when should we expect ordinary least square, which involves:

$$\min_{a,b} \sum_{i=1}^{N} (y_i - a - X_i b)^2$$

and least absolute deviations which solves:

$$\min_{a,b} \sum_{i=1}^{N} |y_i - a - X_i b|$$

If $\mathrm{D(u|X)}$ is symmetric about zero then OLS and LAD both consistently estimate α and β if u is independent of X with E(u)=0, where E(u)=0 is the normalization that identifies α, then OLS and LAD both consistently estimate the slopes, β. If u has an asymmetric distribution, then med(u)≡ $\eta \neq 0$, and $\hat{\alpha}_{\mathrm{LAD}}$ converges to $\alpha + \eta$ because Med(y|X)= $\alpha + X\beta + \mathrm{Med(u|X)} = \alpha + X\beta + \eta$.

But in many application neither of the earlier described approaches is likely to be true mainly because the distribution of y, variance (u/X) is not constant. Therefore, quantile regression is an appropriate techniques because it is much less sensitive than the mean to changes in extreme values. We are interested in how covariates affect quantiles (of which the median is the special case with $\tau = 1/2$), under linearities:

$$Quant_\tau(Y_i|X_i) = \alpha(\tau) + X_i\beta(\tau)$$

Therefore, consistent estimators of $\alpha(\tau)$ and $\beta(\tau)$ are obtained by minimizing the “check” function:

$$\min_{\alpha\epsilon\mathbb{R},\beta\epsilon\mathbb{R}^K} \sum_{i=1}^{N} C_\tau(Y_i - \alpha - X_i\beta)$$

DATA

The data used for this study is obtained from the farm-household survey conducted during 2014/15 by the Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Center (CIMMYT). The data was collected with a purpose of wheat technology adoption analysis and its impacts on smallholder producers. Survey questionnaire was designed and was tested. After pre-testing, the questionnaire was revised. The questionnaire was carefully designed to capture all the most important issues such as household and farm characteristics, agroecological, input use, market, asset ownership, production constraints, access to information and other relevant variables.

The sampling frame covered seven major wheat-growing agro-ecological zones that account for over 85% of the national wheat area and production distributed in four major administrative regions (Oromia, Amhara, SNNP and Tigray) of Ethiopia. A total of 2017 farm households in seven agro-ecological zones, in 26 zones (provinces), 61 woredas (districts) and 122 kebeles/villages were interviewed.

A multi-stage stratified sampling procedure was employed to select villages from each agro-ecology, and households from each kebele/village. First, agro-ecological zones that account for at least 3% of the national wheat area each were selected from all the four major wheat growing. In the second stage of sampling procedure, up to 21 villages in each agro-ecology, and 15 to 18 farm households in each village were randomly selected with proportionate random sampling. Detailed and structured questionnaire were used to collect the data, and trained enumerators were used to ensure collection of quality data (Table 1).

Table 1. Summary of descriptive statistics of major variables used in the econometric models.

Variable	Description of variable	Aggregate mean (SD)
Output and inputs		
Output (wheat yield)	Natural logarithm of wheat output (kg/ha)	1248 (2112)
Land (wheat plot size)	Natural logarithm of cultivated wheat farm (ha)	0.70 (0.72)
Labor	Natural logarithm of man-days per hectare[2]	0.29 (37.5)
Seed	Natural logarithm of quantity of seed used (Kg)	120.4 (164.7)
Fert	Natural logarithm of fertilizer (Dap) used (kg/ha)	57.66 (70.5)
	Natural logarithm of fertilizer (Urea) used (kg/ha)	24.77 (36.4)
Oxen	Natural logarithm of oxen-days used	16.46 (16.5)
Household characteristics		
Wheat EXP	Age of household head in years	17.81 (11.1)
Model farmer (model=1)	Educational level of household head in number of years in schooling	0.42 (0.49)
HHAGE	# of members of the household	45.93 (12.6)
HHSEX (Male=1)	Dummy if training received in wheat production=1	0.919 (0.28)
HHEDU (Read&write=1)	Dummy: If household head is model farmer=1	0.62 (0.48)
FAMILYSIZE	# years of wheat growing experience of household head	6.57 (2.21)
Resources, constraints and market access		
MKTDSTNCE	Walking distance to village markets (min)	9.05 (5.88)
Input mkt	Walking distance to input markets (min)	4.26 (3.84)
TLU	Livestock holding size in Tropical Livestock Unit (TLU)	5.43 (4.40)
Plots	# of wheat plots owned	1.80 (1.06)
Agricultural support services		
Credit	Dummy for participation in credit program (1=credit received)	-
Mobile telephone	Mobile telephone ownership status (1=owned)	-
Ext contact	# of contact with extension worker in a year (2014)	0.96 (0.37)
Training	# of trainings received 2014/15	0.86 (0.34)
Agro-ecologies (reference=Cool humid mid highlands)		
Tepid semi-arid mid highlands	Dummy: Farmer is in Tepid semi-arid mid highlands=1	-
Tepid humid and sub-humid mid highland	Dummy: Farmer is in Tepid humid and sub-humid mid highland=1	-
Tepid moist & sub-moist mid-highland	Dummy: Farmer is in Warm moist and sub-moist lowlands=1	-
Cool moist and sub-moist mid highlands	Dummy: Farmer is in Tepid moist and sub-moist mid-highland=1	-
Warm sub humid lowland	Dummy: Farmer is in Cool moist and sub-moist mid highlands=1	-
Regions (reference=Amhara region)		
Tigray	Dummy: Farmer in Tigray region=1	-
SNNP	Dummy: Farmer in SNNP region=1	-
Oromia	Dummy: Farmer in Oromia region=1	-
Social capital		
Coop member (1=if member to coop)	Dummy: If member farmer is member of input/seed/marketing cooperatives=1	0.98 (0.10)
Trust rader	# of traders that farmers know and trust	3.60 (4.7)
Relatives	# of relatives living inside and outside the village	11.1 (24.8)
Soil fertility status (reference=poor)		

[2] Man-day is calculated based on regular and common working hours in the study areas which is equivalent to 8 h.

Table 1. Contd.

Good	Dummy: Soil fertility if the soil fertility is good in status=1	0.42 (0.1)
Medium	Dummy: Soil fertility- if the soil fertility is medium in status=1	0.46 (0.01)
N	No of observations	1611

*, ** and *** denote significance level at 10%, 5% and 1%, respectively;. SD is standard deviation. Source: Own Survey, 2014/2015.

Table 2. Hypothesis tests (Aggregate model).

Null hypothesis	χ^2 statistics	p value	Decision
Testing there is no technical inefficiency in the model			
$H_o: \gamma = 0$	11.19	0.000	Reject H_o
Testing the null hypothesis that the translog SFPF can be reduced to a Cobb-Douglas SFPF			
$H_o: \beta_{ij} = 0$	0.42	0.21	Not Reject H_o
Test for variables included in the inefficiency model have no effect on technical inefficiency			
$H_o: \delta_1 + \delta_2 +..\delta_8 = 0$	20.31	0.001	Reject H_o

Source: Own computation.

EMPIRICAL ANALYSIS

Importance of wheat in Ethiopia

Wheat is one of the most important cereal crops consumed in different forms in Ethiopia and the rest of the world. Ethiopia is the second largest wheat producer in sub-Saharan Africa (SSA) next to South Africa (Demeke and Marcantonio, 2013) and it ranked 4th after teff, maize and sorghum in terms of area coverage with 1,605,653.9 hectares and 3rd in terms of quantity production with 3,925,174.135 tons in 2013/14 cropping season in Ethiopia (CSA,2014).

Wheat in Ethiopia is grown as a staple food in the highlands at altitude ranging from 1500 to 3000 masl. The largest volume of the main season production of wheat originates from Oromia which constitute around 55% of the country's total wheat production followed by Amhara and SNNP with 29 and 9% respectively. Despite its potential for wheat grain production, Ethiopia falls short of being self-sufficient in wheat production, and is currently a net importer of wheat grain in which much of the domestic wheat demand of flour mill factories is met through imports (FAO STAT, 2014).

The Ethiopian agricultural research system has generated productivity enhancing improved wheat technologies which the national extension system has disseminated during the last couples of decades. Significant number of farmers has accessed these technologies but the national productivity level is still quite low which could be attributed mainly to inefficiencies under the modern technology use. Therefore, understanding the technical efficiency level of farmers in wheat production needs to be analyzed, and factors that cause inefficiencies in wheat production need to be well understood. In addition, information generated in this study will contribute for the existing stalk of knowledge on technical efficiency and factors that affect technical efficiency.

Description of variables

The production technology of sample farmers is represented by Cobb Douglas production function. The Cobb Douglas production function provides adequate representation of the production technology under the study as long as the interest is on measurement of efficiency not on the analysis of the general structure of the production technology (Taylor et al., 1986). Despite this, the generalized likelihood ratio test[3] were used to test Cobb-Douglas functional form is the right functional form than the translog. Likelihood ratio test have confirmed that the Cobb Douglas functional form is true representation of the data collected from the study areas (Table 2).

As both Cobb Douglas and Translog functional forms do not to satisfy linearity in parameters, taking logarithms of both sides of the equation is a common practice to make them amenable to estimation using linear regression as a result observation that have zero value for any of the variables included in the model are dropped due to the fact that it is impossible to construct logarithm using variable that contain zero (Coelli et al., 1998). Therefore, the Cobb-Douglas functional form used is specified as follows:

[3] Likelihood Ratio (LR) statistics are only asymptotically justified, hence they can only be relied when the sample size is big.

$$lnY_i = \beta_0 + \beta_1 \ln land + \beta_2 \ln labor + \beta_3 \ln fertil izer + \beta_4 \ln seed + \beta_5 \ln Oxenday + (v_i - u_i) \quad (4)$$

where ln denote the natural logarithm; Y_i denote the total quantity of wheat output produced by household i in kilogram; $land$ denote the total land planted with wheat in $hectares$; $labor$ denote the amount of family labor in mandays; and was calculated as indicated onn Annex 4 using a conversion factor suggested by Storck et al. (1991); $fertilizer$ denotes the amount of both Dap and Urea added together in kilogram; $seed$ denote the quantity of seed utilized in kilogram; $oxendays$ represent the number of days oxen are used in producing the wheat measured in oxendays. However, as the number of farmers that use pesticide and herbicide in the 2014, production season was very small and the chemical is excluded from the model specified earlier, and this can be considered as the limitation of the study (Table 1).

Empirical results

The study hypotheses were stated in null terms. The first null hypothesis that describes inexistence of technical inefficiency among wheat producers is rejected. As pointed out by Coelli and Battese (1995), if a null hypothesis includes $\gamma = 0$ then the statistic has asymptotically a mixed Chi-squared distribution, since by its definition γ has to be non-negative.

In the third null hypothesis, we stated that the variables included in the inefficiency effect model have no effect on the level of technical inefficiency. This null hypothesis is also rejected for wheat producers, showing that the joint effect of these variables on technical inefficiency is statistically significant. Estimates of the model parameters were computed using the frontier model with a Cobb-Douglas functional form. The real investigations for the occurrence of inefficiency were calculated by estimating the stochastic frontier production function and conducting a likelihood-ratio test assuming the null hypothesis of no technical inefficiency. This test statistic is computed using *STATA software version 13*.

The technical efficiency and the factors influencing technical efficiency were examined by fitting a frontier production function model including the explanatory factors of technical efficiency Table 3 shows the presentation of the parameters estimates and related statistical test obtained from the stochastic frontier production function analysis for wheat producers. The likelihood ratio test for the null hypothesis $H_o: \gamma = 0$ is rejected indicating the presence of statistically significant variation among wheat producers that can be attributed to inefficiency. The lamda (λ) value is also greater than one which confirms the presence of inefficiency.

Wheat production of sample famers was represented by a Cobb-Douglas Stochastic Frontier Model, and half normal distribution of inefficiency. Because, a series of preliminary likelihood ratio tests revealed that Cobb Douglas stochastic frontier model best fit the data given the more flexible translog frontier model, and the distribution of inefficiency best represented by the half-normal distribution. The natural logarithms of the data on the input and output variables were taken for efficiency analysis. Table 4 shows estimated coefficients of land, labor, seed fertilizer and oxen for stochastic frontier model of Cobb-Douglas production function. The coefficients associated with the inputs measure the elasticity of output with respect to inputs. Positive and significant values indicate that there is a potential for increasing production or output of wheat by increasing the level of inputs used in the production process.

Estimates of production frontier for wheat producing farmers are presented in Table 4. In aggregate, all inputs except labor is found to be significantly and positively affecting wheat output indicating that there exists still potential for increasing level of output by increasing usage of these inputs.

Technical efficiency levels

Three dummy variables for regions were included in the inefficiency model representing Tigray, Oromia and SNNP region compared with Amhara region. The negative and significant value of coefficients for Tigray and Oromia regions at 1 and 5% level, respectively indicates lower inefficiency (higher mean efficiency) compared to Amhara region. Aggregate of all regions, the greatest proportion of wheat producing farm households fall in the range of 60 to 80% technical efficiency level

Determinants of technical efficiency: Quantile regression and maximum likelihoods (ML) estimates compared

Maximum likelihoods (ML) summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function E(y|x). This provides only a partial view of the relationship. But a more comprehensive picture of the effect of the predictors on the response variable can be obtained by using Quantile regression.

Quantile regression models show the relation between a set of predictor variables and specific percentiles (or quantiles) of the response variable. It specifies changes in the quantiles of the response. QR is more robust to non-normal errors and outliers and hence appropriate for response variable (technical efficiency) used in this study as it has outlier values both in agreegate and for each regions (Annex 1 and 2). Standard errors and confidence

Table 3. Maximum likelihoods estimate for wheat production frontier function and inefficiency model.

Variable	Coefficient	t-value
$Constant$	4.92	(27.76)***
$\ln LAND$	0.43	(10.69)***
$\ln LABOR$	-0.03	(-1.70)
$\ln OXENDAYS$	0.069	(2.29)*
$\ln SEED$	0.361	(12.41)***
$\ln FERTILIZER$	0.188	(8.20)***
σ_v^2	-1.813	-19.78***
Function coefficient	1.01	-
λ	1.73	-
Constant	-0.120(-0.28)	-
Log likelihood	-1165.1	-
N	1465	-

***, **, * indicate significance at 1, 5 and 10% levels, respectively.

Table 4. Efficiency estimate by regions.

Efficiency estimate	Proportion of sample HHs disaggregated by regions (%)				
	Tigray	SNNP	Amhara	Oromia	Aggregate
≤ 0.1	-	0.62	0.43	-	0.20
> 0.1 *and* ≤ 0.2	1.25	0.62	1.08	0.39	0.68
> 0.2 *and* ≤ 0.3	2.5	2.48	3.23	1.45	2.18
> 0.3 *and* ≤ 0.4	-	7.45	3.66	3.68	3.89
> 0.4 *and* ≤ 0.5	2.5	6.21	9.48	5.39	6.62
> 0.5 *and* ≤ 0.6	10	17.39	16.81	9.21	12.56
> 0.6 *and* ≤ 0.7	18.75	31.06	27.16	21.97	24.44
> 0.7 *and* ≤ 0.8	38.75	21.12	29.74	35.13	32.08
> 0.8 *and* ≤ 0.9	21.25	13.04	8.41	22.63	17.00
> 0.9 *and* ≤ 0.99	5	-		0.13	0.34
Mean efficiency	**0.71**	**0.62**	**0.62**	**0.72**	**0.66**
Maximum	0.92	0.88	0.15	0 .94	0.92
Minimum	0.19	0.07	0.094	0.12	0.05
St.dev	0.13	0.15	0.17	0.13	0.14

limits for the quantile regression coefficient estimates can be obtained with asymptotic and bootstrapping methods. Both methods provide robust results (Koenecker and Hallock, 2000), with the bootstrap method preferred as more practical.

Quantile regression allows comparing how some percentiles of the technical efficiency may be more affected by certain socioeconomic characteristics than other percentiles. Coefficient estimates for the 25, 50, 75 and 95th quantile regression, and the ML estimates for technical efficiency are presented in Table 5. The ML and quantile regression estimates of the factors affecting technical efficiency are provided in Table 5. Variations in technical efficiency among wheat producer farmers are hypothesize to be due to farm and farmers attributes which reflect managerial ability of farmers and their access to information. The ML estimated coefficients[4] for age is positive and significant implying that efficiency decrease with increase in age. Technical efficiency was significantly but negatively affected by age at 25th and 50th quantile while have no effect at higher quantile level (75th and 95th). The main reason might be that while

[4] In the inefficiency model specification, it is well understood that a negative sign on a parameter explaining inefficiencies means that the variable is improving technical efficiency, while for a positive sign, the reverse is true.

farmers are getting older they tend to less likely shift from their long adapted practices to new practices, hence declining technical efficiency. This finding is in conformity with findings of Tolesa et al. (2014), Arega (2003) and Ajibefun (2002). Contrary to this finding, Coelli and Battese (1995) reported farmers with older age were technically more efficient. Llewelyn and Williams (1996) observed that technical efficiency increases up to a certain age level and then eventually declines. This indicates that age has mixed impact on efficiency and may be depending on crop and study area.

The ML estimate for the effect of being a model farmer on technical efficiency was insignificant, while the quantile regression estimate revealed being a model farmer have significant impact at 10% level on technical efficiency at 25, 50 and 95th quantiles and at 1% significance level at 75th quantile. This indicates deficiency of ML estimation techniques which masked the real effect of the dummy variable *model farmer* in improving technical efficiency.

Mobile ownership has exhibited highly significant influence, at 1% level, on technical efficiency. Farmers that have mobile telephone were found to be more technically efficient *vis-a-vis* farmers who don't have mobile and the main reason might be due to the very instrumental role mobile is playing in improving farmers access for such information as new agricultural practices, market information, input sources and application methods from various sources mainly from development agents, other farmers, traders, and knowledge sources such as agricultural researchers and experts.

Similar results were reported by Falola and Matthew (2013) which indicated positive and significant impact of mobile telephone on technical efficiency of farmers in Nigeria; and other similar studies such as Aker (2008) study on the impact of introduction of cell phones on grain trade throughout Niger and Getaw, and Godfrey (2015) study on the impact of mobile phones on farmers' marketing decisions and prices they receive have reported positive and significant impact of mobile telephone.

Total Livestock Unit (TLU) as calculated by a conversion factor suggested by employing Storck et al. (1991) as indicated on Annex 3 is significant factor in improving technical efficiency. This is because livestock have direct implication on technical efficiency as it is major source of draft power during plowing and weeding, and means of transporting inputs from market to the farm, as a result households could carry out farm operation at the right time and right frequency (such as plowing and weeding). Apart from these, the higher number of total TLU owned implies the household capacity to procure inputs (seed, fertilizer and all other inputs) at the right time so that it could be made available in time which contributed in increased output. This is also consistent with findings of various studies such as Beyan (2014), Tolesa et al. (2014) and Temesgen and Ayalneh (2005). Livestock ownership measured in TLU is underestimated in ML estimate compared to the quantile regression which turned estimates at all quartiles when it becomes highly significant at 1% level.

The insignificant level of influence of credit on technical efficiency as estimated by ML technique was turned out to be significant at 25 and 50th level when employing quantile regression technique. This indicate that credit have significant influence on technical efficiency of farmers at lower level of technical efficiency than those at higher level. Financially, constrained farmers who lack also access to credit will have problem of undertaking farm operations timely and also may fail to optimize input use thereby affecting their level of technical efficiency. This is inconformity with the findings of Arega (2003), Tolesa et al. (2014) and Njeru (2010).

Significant variations in technical efficiency level were observed among the different regions, Tigray and Oromia region being the most efficient compared to Amhara and SNNP which could be attributed to the effectiveness of extension service in Tigray and Oromia which enabled farmers apply recommended practices properly. The remaining variables model farmer, training and education were insignificant.

Cooperative membership has significant influence on technical efficiency especially among those farmers at 95th quantile level. Cooperatives are key economic organizations that provide input and output market access which in turn improve farmers access to various agricultural information necessary for proper application of technologies.

Agro ecological differences are important factors that affect efficiency and there exists significant differences in technical efficiency among wheat producing farmers at all quantile levels. This is because wheat is affected by agro ecological variations which have an implication for identifying niches that is highly suitable for wheat production. Cool humid mid highlands and Cool moist and sub-moist mid highlands are the most suitable niches for wheat production.

CONCLUSION AND RECOMMENDATIONS

The objective of this study was to measure the level of technical efficiency of wheat producing farmers in the four major regional states, and identify the sources of technical inefficiencies. A Cobb-Douglas model was used to determine levels of technical efficiency and the analysis of its determinants were done using both ML and quantile regression techniques.

Wheat producing farmers in Tigray, SNNP, Amhar and Tigray regional states have experienced significantly high level of technical inefficiencies which indicated the existence of enormous potential for increasing productivity using the current level of technology. By strengthening the extension service delivery, government can achieve higher wheat yield through improving

Table 5. Quartile regression and ML estimates compared.

Variable	ML Estimates[5]		Quantile regression estimates[6]							
			(25th)		(50th)		(75th)		(95th)	
	coefficient	t-value	Coefficient	t-value	Coefficient	t-value	coefficient	t-value	coefficient	t-value
Household characteristics										
Wheat EXP	0.0177*	(2.49)	-0.0116	(-1.29)	-0.478	(-0.89)	-0.364	(-0.99)	-0.0645	(-1.23)
Model farmer	-0.180	(-1.32)	0.0257*	(2.02)	0.0228*	(2.38)	0.0201***	(4.44)	0.0164*	(2.56)
HHAGE	0.0116*	(1.77)	-0.00269***	(-3.65)	-0.00153***	(-3.53)	-0.000255	(-0.65)	-0.000374	(-0.74)
HHSEX	-0.015	(-0.07)	0.0171	(0.89)	0.00335	(0.32)	0.0115	(1.18)	-0.00203	(-0.19)
HHEDU	0.155	(1.05)	-0.0149	(-0.97)	-0.00994	(-1.33)	0.00691	(0.97)	0.0134	(1.11)
Family size	0.019	(0.68)	-0.896	(-0.07)	0.385	(0.28)	0.0196	(0.15)	0.00123	(0.87)
Resources, constraints and market access										
MKTDSTNCE	-0.0940	(-0.84)	-0.0751	(-0.60)	-0.0646	(-1.30)	-0.00339	(-0.74)	-0.309	(-0.67)
INPUTMKT	0.0327*	(1.90)	-0.0457**	(-2.59)	-0.0118	(-1.41)	-0.00123	(-1.63)	-0.545	(0.72)
TLU	-0.0471*	(-2.22)	0.00920***	(9.79)	0.00658***	(5.74)	0.00413***	(5.18)	0.00389***	(4.29)
Plots	-0.281**	(-3.02)	0.0295***	(7.28)	0.0206***	(7.04)	0.0104***	(3.37)	0.00877**	(2.98)
Agricultural support services										
Credit	-0.282	(-1.03)	0.0395*	(2.28)	0.0210*	(1.98)	0.00862	(1.06)	0.00668	(0.76)
Mobile telephone	-0.493***	(-3.34)	0.0936***	(7.00)	0.0750***	(10.60)	0.0677***	(8.64)	0.0368***	(4.78)
EXT contact	0.01	(0.76)	0.0205	(1.39)	0.499	(0.59)	0.115	(0.7)	0.00201	(0.12)
Training	-0.0825	(-0.43)	0.0197	(0.94)	0.00520	(0.44)	0.0159	(1.19)	0.00595	(0.49)
Social capital										
Coop member	-0.0349	(-0.02)	0.0161	(0.11)	0.0118	(0.94)	0.0123	(0.51)	-0.0447***	(-4.79)
Trust rader	-0.0229	(-0.59)	0.000705	(0.19)	-0.000782	(-1.38)	-0.00124	(-0.74)	0.296	(1.75)
Relatives	-0.907	(-1.54)	-0.909	(-0.83)	-.106639	(0.027)	0.902	(1.15)	-0.0544	(-0.76)
Soil fertility status										
Soilfert_medium	-0.417*	(-2.51)	0.0721***	(4.52)	0.0496***	(5.35)	0.0738***	(8.09)	0.0229*	(2.38)
Soilfert_good	-0.803***	(-4.48)	0.133***	(8.23)	0.0925***	(9.75)	0.0423***	(4.81)	0.0138	(1.44)
Agro ecologies (Cool humid mid highlands=0)										
Tepid semi-arid mid highlands	-2.227*	(-2.21)	-0.195***	(-4.59)	-0.155***	(-6.85)	-0.124***	(-6.43)	-0.0674**	(-3.06)
Tepid humid and sub-humid mid highland	2.284*	(2.50)	-0.154***	(-3.36)	-0.131***	(-5.38)	-0.110***	(-5.14)	-0.0663**	(-2.78)
Tepid moist and sub-moist mid-highland	2.067*	(2.38)	-0.227***	(-5.43)	-0.170***	(-7.65)	-0.123***	(-6.44)	-0.0584**	(-2.73)

[5] Negative sign of the coefficient indicate the variable have positive effect on technical efficiency and vice versa.
[6] Negative sign of the coefficient indicate the variable have negative effect on technical efficiency and vice versa.

Table 5. Contd.

Cool moist and sub-moist mid highlands	1.621	(1.93)	-0.861	(-0.19)	-0.0122	(-0.50)	-0.698	(-0.33)	0.0140	(0.62)
Warm sub humid lowland	2.313*	(2.45)	-0.262***	(-4.82)	-0.254***	(-8.69)	-0.183***	(-6.94)	-0.158***	(-6.98)
Regions										
Tigray	1.015***	(3.90)	0.104**	(3.06)	0.117***	(7.65)	0.0872***	(6.70)	0.0708***	(6.02)
Oromia	0.520***	(3.79)	0.0768***	(4.65)	0.0476***	(6.11)	0.0508***	(6.84)	0.0260***	(3.35)
SNNP	0.0576	(0.26)	-0.0112	(-0.50)	-0.00390	(-0.31)	0.0123	(1.09)	0.00780	(0.69)
_cons	-	-	0.660***	(23.15)	0.721***	(41.93)	0.734***	(43.97)	0.847***	(32.9)
N	1444	-	1444	-	1444	-	1444	-	1444	-

production practices, and then reducing the burden on the meager foreign currency the government is spending to import wheat from abroad. ML estimation techniques either overestimate or underestimate real effect of the different socioeconomic variables on technical efficiency, especially when the dependent variable (technical efficiency) has skewed distribution. For instance, ML technique underestimated a variable 'model farmer' as having insignificant effect on technical efficiency while the quantile regression estimate revealed significant effect of the variable on technical efficiency. Similarly, credit participation influence was underestimated by ML techniques but the quantile regression have revealed that credit participation in fact have positive and significant influence on technical efficiency. Therefore, a more comprehensive picture of the effect of the various socioeconomic variables on technical efficiency variable can be obtained by using Quantile regression, than ML estimation technique.

Using quantile regression credit participation, number of wheat plots owned, number of livestock owned and mobile ownership have positive and significant impact on technical efficiency while age has significant but negative influence on technical efficiency, while wheat growing experience, training and education level have no significant influence on technical efficiency.

Conflict of Interests

The authors have not declared any conflict of interests.

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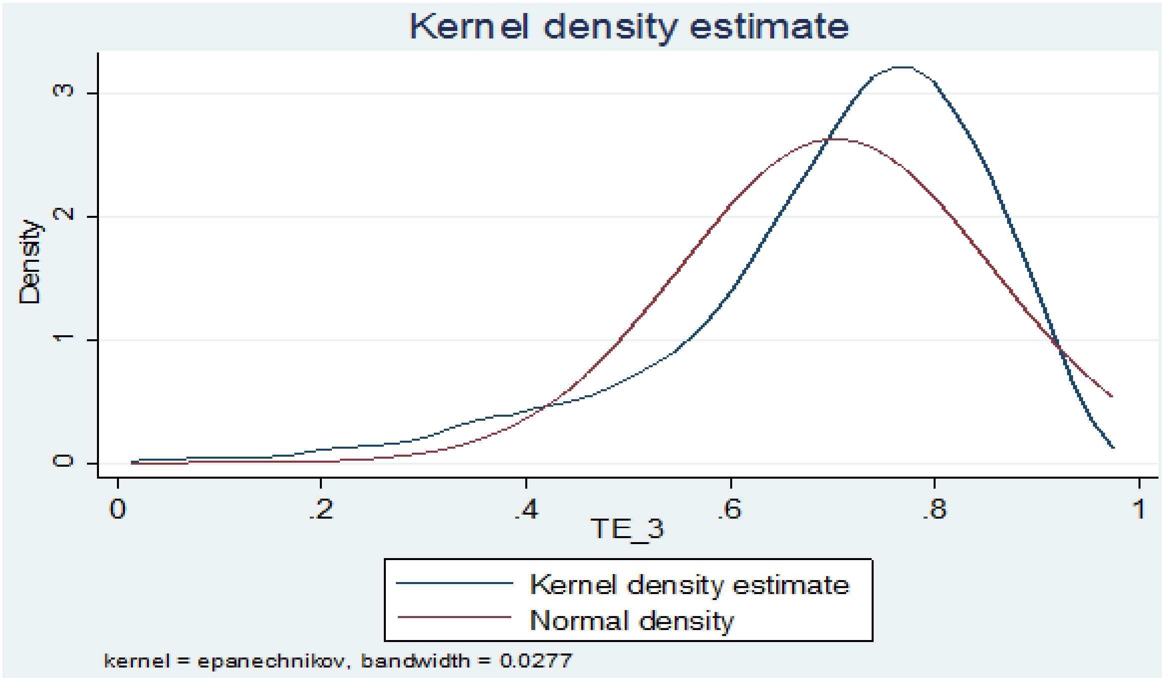
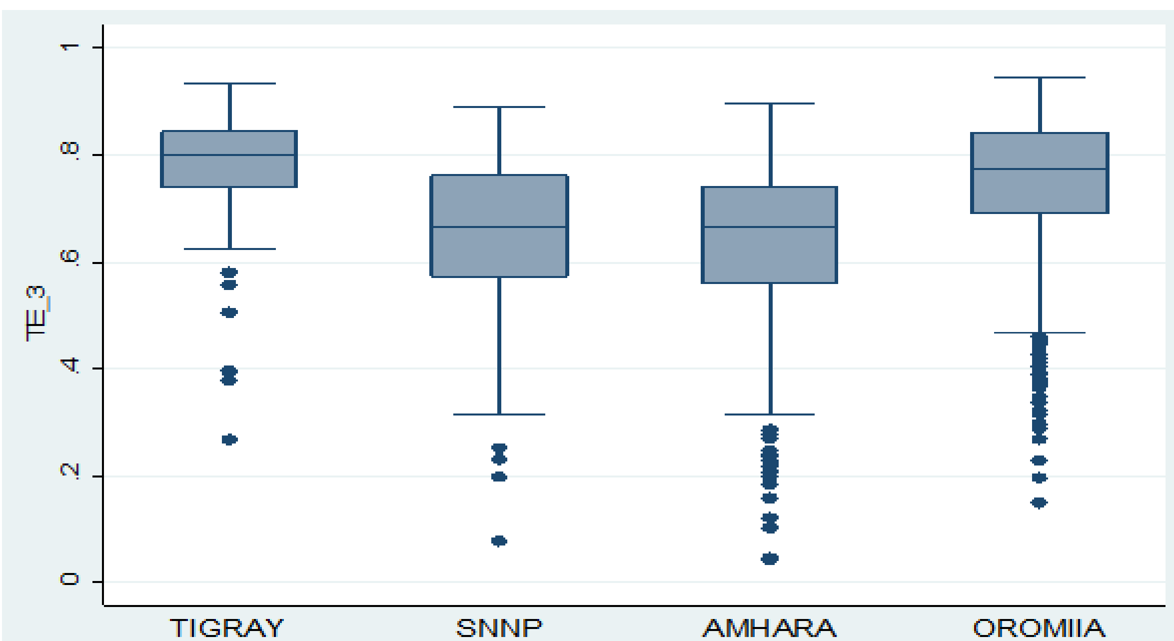
ANNEX



Annex 1. Kernel density distribution of technical efficiency (aggregate of all regions).



Annex 2. Distribution of technical efficiency by regions.

Annex 3. Conversion factor for total livestock unit.

Livestock type	Conversion factor(TLU)	Livestock type	Conversion factor(TLU)
Calf	0.25	Donkey(young)	0.35
Wearned calf	0.75	Camel	1.25
Cows and oxen	1.00	Sheep and Goat(Adult)	0.13
Horse	1.10	Sheep and goat(Young)	0.06
Donkey(Adult)	0.7	Chicken	0.013

Source: Storck et al. (1991).

Annex 4. Conversion factor for man-equivalent.

Age groups (Years)	Male	Female
<10	0	0
10-13	0.2	0.2
14-16	0.5	0.4
17-50	1.0	0.8
>50	0.7	0.5

Source: Storck et al. (1991).