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AN ANALYSIS OF THE EXTENT AND CAUSES OF THE TECHNICAL EFFICIENCY OF FARMERS GROWING CEREALS IN ETHIOPIA: EVIDENCE FROM THREE REGIONS

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ABSTRACT: Technical inefficiency (TI) indicates that output gains may be possible in the short term. A study on the main determinants of technical efficiency (TE) provides valuable information to policy makers and indicates ways of formulating appropriate strategies of agricultural development. This paper measures the degree of technical efficiency of farmers growing cereals in five of the sites (Adaa, Daramalo, Kersa, Shashemene and Yetmen) covered by the Ethiopian Rural Household Survey. Using the approach developed by Aigner, Lovell and Schmidt (1977), we estimated a stochastic frontier production function using MLE (Maximum Likelihood Estimation) and COLS (Corrected Ordinary Least Squares). Due to its popularity in applied work on agriculture, we chose the Cobb-Douglas (C-D) technology. Our results show that land quality and the average age of household members engaged in agriculture are important variables in explaining output variation among farmers. In addition, regional differences are large and highly significant. With regard to causes of TE, we note that sharecroppers are, on average, more efficient. Since, within the group of sharecroppers there is much variation a more detailed study is required to shed light on this finding.

1. INTRODUCTION

For Sub-Saharan Africa, the productivity of both land and labor declined between 1973 and 1984. There are various reasons for this: policy problems, and farm level inefficiencies are few among many.

According to Hayami and Ruttan (1984) and Timmer (1988), differences in agricultural productivity can stem from a variety of factors:

1. Different endowment of internal resources, such as land and livestock;
2. Different use of technical inputs, such as fertilizers and mechanical devices;
3. Different investment in human capital through general and technical education and

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4. Different size of farms, which might generate economies and diseconomies of scale.

Ethiopian agriculture is stagnating in both measures of agricultural productivity viz. land and labor productivity. Ethiopia's agricultural sector is unable to meet one of its most basic and important functions: the provision of food for the large and rapidly expanding population. Agricultural growth averaged 2.2% during the 1960s, but dropped to 0.7% in the 1970s and a mere 0.5% in the 1980s. Crop yields have stagnated at about 1 ton per hectare since the early 1970s. With the doubling of the population between 1970 and 1990, the per capita food production has sharply declined and the country has become increasingly dependent on food aid in recent years.

Agriculture today is at the heart of the Ethiopian government's drive to improve the livelihood of the rural population. Part of the on-going debate on how to transform agriculture focuses on improved technology, input levels and credit allocation. While such objectives are imperative, it is also of considerable interest to understand how far the farmers are from the production frontier in the first place (or in the jargon, what the level of technical efficiency (TE) is[1]). The reasons for this interest are; i) TI indicates that output gains may be possible in the short term, and; ii) credit for the purpose of adoption of new technologies and higher input levels will be more successful (and depending on the degree of TI perhaps substantially so) the more efficient farmers are.

The arguments for points i) and ii) above are as follows: consider that there are two farmers, A and B. Both use the same level of inputs (both fixed and variable) and both face identical production environments[2] , but they do not achieve the same output levels. If farmer A achieves less output than B then we term A as technically inefficient, relative to farmer B. With regard to point i), if we can understand what drives this difference in TE, then farmer A's output could be raised without any increase in inputs. If, for example, it is lack of information that accounts for the discrepancy it is likely that output gains could be attained in a relatively short time period. While the actual story is bound to be more complex it will still be true that certain policies which are (relative to, for example, providing credit or subsidized fertilizer) less costly and may generate short term gains.

With regard to point two above , if both farmers obtain credit so as to acquire improved seeds, oxen and/or fertilizer then it is likely that farmer B will still outperform farmer A. In this sense the effect of the attempted transformation will be dampened and some (additional) resources will be wasted.

A decline in agricultural production can be caused by a sub-optimal utilization of the existing technology or due to technical inefficiency. A study on the main determinants of TE provides valuable information to policy makers and they can adopt the appropriate strategies of agricultural development.

Ethiopian farmers suffer from a lack of basic inputs such as credit, fertilizers, land and so on. The scarcity of inputs serves as a strong motivation to farmers to make the best use of the available inputs. But how? Studies that focus on indicating how effectively inputs can be put in to production to gain the maximum benefit out of them are greatly required.

In the first part of this paper, we will measure the degree of technical efficiency of cereal growing farmers in five of the sites covered by the Ethiopian Rural Household Survey. We note that work on this topic on Ethiopia is rare. In the second part we provide a discussion of the concept of the frontier production function which is a popular tool to measure TE. In the third part, the estimation of such a model is described. The data is presented in part four and results are given in part five. Part six concludes the paper.

2. THE MODEL

The modeling and estimation of frontier production functions has been an important area of econometric research during the last two decades. The seminal paper which has provided the stimulus to this research was that by Farrell (1957). However, the concept did not become widely used until: i) the stochastic frontier production function was introduced in 1977, and ii) it became possible to solve for individual technical efficiency in 1982. Following these advances this methodology has found application in a wide variety of areas such as agriculture, industry, health care, and banking, to mention but a few.

Below we give a brief survey of the concepts. For more detail see the surveys by Forsund, Lovell and Schmidt (1980), Schmidt (1985), Fare, Grosskopf and Lovell (1985), Bauer (1990), and Lovell (1993). Battese (1992) is a survey with special reference to agriculture. In our exposition we discuss only statistical parametric methods. We do not attempt to cover the topic of Data Envelopment Analysis (DEA) which has also become a widely used method.[3]

2.1 Deterministic Frontiers

Initially the discussion revolved around deterministic frontiers. A deterministic frontier is defined by :

$$y_i = f(x_i, \beta_k)e^{-u_i} \qquad [1]$$

where y_i denotes the actual output level; x_i is a vector of inputs; β_k is a vector of k parameters; u_i is a one-sided, non-negative, random variable associated with farm-specific factors which keeps the farm from attaining maximum output; and the subscript i denotes the ith farm.

The term $\exp(-u_i)$ lies between 0 and 1 and gives a measure of technical efficiency. To show this, we may write (1) as:

$$\frac{y_i}{f(x_i, \beta_k)} = e^{-u_i} \qquad [2]$$

such that $\exp(-u_i)$ is the ratio of actual to potential output.[4] Once an actual functional form has been imposed on (2) the equation may be estimated by OLS or MLE.

It has been shown that OLS provides consistent estimates of all the parameters except for the constant term. This must then be corrected by subtracting the mean of u[5]. Unfortunately, after correcting the constant term, some of the residuals may still be negative. A simpler technique is to subtract the largest positive residual from the constant term (also yielding a consistent estimate[6]). This generates one farm with u=0, i.e. exp(-u)=1, (or multiplied by 100=100% technically efficient). It is this farm which defines the maximum possible output for the given technology and sample. The rest of the sample is termed inefficient relative to this farm.[7]

To estimate a deterministic frontier by MLE one must first make a distributional assumption about u. It is important to note here that the range of the dependent variable depends on the parameters to be estimated. Hence, one of the regularity conditions used to show that MLE is consistent and asymptotically efficient is violated (see Greene 1980b). This means that the half-normal and exponential distibutions cannot be used. Greene shows that the gamma density has the desired properties, and is therefore useful.

An important drawback of deterministic frontiers is that all the deviation from the frontier is labeled as technical inefficiency. This is unrealistic (and now unnecessary) and we turn to a discussion of the more popular stochastic frontiers.

2.2 Stochastic Frontiers

In an independent work Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) suggested to allow for some random variation across the frontier. The essential idea behind the stochastic frontier model is that the error term is composed of two parts. A symmetric component (which we will always denote by v) permits random variation of the frontier across production units. It captures measurement error, other statistical noise and random shocks outside the control of the production unit. A one-sided component (which we will denote by u) captures the effects of inefficiency relative to the stochastic frontiers.

This model is written as:

$$y_i = f(x_i, \beta_k) e^{v_i - u_i} \qquad [3]$$

where $f(x_i, \beta_k)$ is the deterministic kernel; and $f(x_i, \beta_k)\exp(v_i)$ is the stochastic frontier. Technical efficiency relative to the stochastic production frontier is captured by the one-sided error component, $\exp(-u_i)$. Such a stochastic production frontier may be estimated by COLS or MLE[8]. Whichever estimation technique is used, the distribution of u_i must first be specified.

Initially, only average estimates of u were derivable. It was not until the contribution by Jondrow, Lovell, Materov and Schmidt (1982) that it is possible to derive farm-by-farm estimates of technical efficiency from the stochastic frontier estimates. Jondrow *et al* (1982) suggest to use the information contained in e_i (where $e_i = v_i - u_i$) to obtain an estimate of u_i[9] (Details about this are given in the section on estimation.) Following this development, this approach became exceedingly popular in the empirical literature.

2.3 Developments

While we do not attempt to provide a through survey of the subject, we believe it is useful to identify several important developments on the topic of technical efficiency.

Initially extensions of the basic model focused on generating more flexibility in the distributional assumptions made about u_i. Stevenson (1980) suggested a generalized stochastic frontier model where the assumption of a zero mean of u_i is relaxed. Greene (1980a) relaxed the assumption of a Cobb-Douglas technology by introducing a flexible functional form. Beckers and Hammond (1987) and Greene (1990) modeled the one-sided error term using the gamma distribution.

Following the formulation of the stochastic frontier, there came the simultaneous estimation of allocative and technical efficiency. Initially Schmidt and Lovell (1979) formulated this problem in a cost minimizing setting. Kumbhakar (1987) modeled technical and allocative efficiency in a profit maximizing framework.

Much of the recent work is focusing on applying panel data in estimating technical efficiency. This is particularly interesting in that it is then no longer necessary to make a distributional assumption for u_i.

The following paragraph gives a review of some technical efficiency studies on Ethiopian farmers. An attempt is made to indicate the methods used and the results obtained by those studies.

Assefa and Heidhues (1996) made an analysis of production efficiency of small holders in the Central Highlands of Ethiopia. They fitted a Cobb-Douglas stochastic frontier production function to cross-sectional data collected on 192 farm households. The reported results indicate that human labor, animal track power and fertilizer are the most important factors affecting productivity.

Using the first round data of the Ethiopian Rural Household Survey of 1993, Mulat and Croppenstedt (1997) adopted a mixed fixed-random coefficients regression model to estimate farm and input-specific measures of TE. In their analysis 342 farm households that practice ox-plough cultivation of cereals are incorporated. They found that human capital, such as literacy and experience are important productivity increasing variables. In addition, a high degree of farm-specific technical inefficiency is observed. Time spent collecting fuelwood and adverse events for livestock were found to be affecting TE.

Abrar (1995) applied Data Envelopment Analysis (DEA) for measuring the efficiency of small holders in three villages of Ethiopia. He used the first round data of the Ethiopian Rural Household Survey. His results show that farmers are more technically inefficient than scale inefficient.

With reference to Eastern Africa we note that work on this topic is rare. Aguilar and Bigsten (1994) use a deterministic frontier model to analyze efficiency differences of small-holder farmers in Kenya. Shapiro and Mueller (1977) considered the sources of technical efficiency of cotton farmers in Tanzania, using a deterministic frontier mode. For some preliminary work on Ethiopian agriculture see Dejene, Croppenstedt and Mulat (1994) and Croppenstedt and Mulat (1994)[10].

3. ESTIMATION OF THE MODEL

In this paper, we followed the approach developed by Aigner, Lovell and Schmidt (1977). The stochastic frontier production function is given as:

$$y_i = f(x_i, \beta_k)\exp(e_i) \qquad [4]$$

where y_i is output; the x_i are a vector of inputs; e_i is our composed error term, composed of the two terms v_i and u_i; and the subscript i refers to the ith farm.

Apart from making a distributional assumption for the error term u, we also need to impose a functional form for the production function. Our choice of the Cobb-Douglas (C-D) technology is guided by two facts: i) it has been very popular in applied work on agriculture in developing countries, and hence our results can easily be compared with previous studies; ii) it fits well even for smaller data sets[11].

Substituting the C-D functional form into equation (4) we obtain:

$$y_i = \beta_0 \prod_k x_{ki}^{\beta_k} e^{v_i - u_i} \qquad [5]$$

where: the y, x, v, u and the subscripts are as described above.

Upon transformation into logarithms we can use either COLS or MLE techniques to estimate (5). We use the latter technique as we can estimate the constant term σ^2 and λ (see below) together and, hence, improve the efficiency of the estimates[12]. To use MLE we need to make a distributional assumption for the two components, v and u. The term v is always assumed to be independently and identically distributed (iid) as $N(0, \sigma_v^2)$. For the u term the most popular choice has been the half-normal distribution i.e. u is distributed iid $|N(0, \sigma_u^2)|$.[13] We adopt this specification because it is easy to implement and the results lend themselves more readily for comparison.

The resulting log-likelihood function is written as:

$$\ln L = \frac{-N}{2}\ln\left(\frac{2}{\pi}\right) - N\ln\sigma + \sum_{i=1}^{N}\ln[1 - F(e_i\lambda\sigma^{-1}] - \frac{1}{2\sigma^2}\sum_{i=1}^{N}e_i^2 \qquad [6]$$

where:

F(.) is the cumulative distribution of the standard normal evaluated at $e\lambda/\sigma$; $\sigma^2 = \sigma_u^2 + \sigma_v^2$; and $\lambda = \sigma_u/\sigma_v$.

Farm-by farm level estimates of u may be obtained using Jondrow et al's suggestion of using the conditional distribution of u, given e. The mean of this distribution can be used as a point estimate of u:

$$E[u_i \mid e_i] = \sigma^*[\frac{f(e\lambda/\sigma)}{1 - F(e\lambda/\sigma)} - \frac{e\lambda}{\sigma}] \qquad [7]$$

where: $\sigma^* = \sigma_u\sigma_v/\sigma$.

For completeness we briefly outline estimation when using the COLS approach. We first run OLS on (5). The resulting residuals are then used to obtain estimates of σ_u^2 and σ_v^2 from the second and third moments of the error term. The formulas, derived in Greene (1982) are:

$$\hat{\sigma}_u^2 = \left[\sqrt{\frac{\Pi}{2}}\left(\frac{\Pi}{\Pi - 4}\right)\left(\sum_i\left(\frac{e_i}{N}\right)^3\right)\right]^{2/3} \qquad [8]$$

$$\hat{\sigma}_v^2 = \sum_i \frac{e_i^2}{N}\left(N - \left(\frac{\pi - 2}{\pi}\right)\hat{\sigma}_u^2\right) \qquad [9]$$

Where: N denotes the number of observations. The constant term is corrected by subtracting $-\sqrt{\frac{2}{\Pi}}\,\sigma_u$

Table 1 Site Specific Characteristics

Characteristic	Adaa	Daramalo	Kersa	Shashemene	Yetmen
Climate	Woyena Dega[a]	Kola[b]	Woyena Dega	Woyena Dega	Woyena Dega
Dominant Crop	Cereals	Cereals	Cash Crops (Chat & Cereal)	Cereals	Cereals
Households	98	74	98	102	61
Use of Fertiliser	Common	Common (Irrigation)	Common	Common	Common
Status of Farmers	Rich	Poor	Rich	Rich	Moderately Rich
Soil Erosion	No	No	Yes-Not serious	No	No
Terrain	Flat	Flat	Flat	Flat/Hills	Flat
Farming Technology	Ox Plough	Ox Plough/ Irrigation	Ox Plough	Ox Plough	Ox Plough
Landless Households[c]	13	3	7	1	3
Female Headed households[c]	23	3	24	17	10

a) Woyena Dega is used to represent a mild weather which is neither very hot nor very cold.

b) Kola is used to represent a hot climate, i.e. arid. (c) Number in survey.

4. THE DATA

In this study we use data on cereal[14] growing farmers in five of the sites covered by the first round (1993/94) of the Ethiopian Rural Household Survey (ERHS)[15]. Further disaggregation is not possible as inputs are given only as aggregates. The five sites are Shashemene, Kersa, Daramalo, Yetmen and Adaa. Shashemene, Kersa and Adaa all lie in Region 4, while Yetmen is in Region 3 and Daramalo in Region 9. For some sites specific characteristics, see table 1. In all we have information on 431 households, but various selection criteria mean that we end up with a final sample of 249 households.[16] A description of the variables used is given below:

Y	Total value of grain output in Meher season, in Birr.
A	Land cultivated under grain crops in Meher season, in Hectares
L	Total number of person days used for ploughing and weeding.
F	Amount of fertilizer applied, in Kilograms.
OX	Number of Oxen and Bulls owned by the household.
LQ	Average quality of the land cultivated, 1-3, 1 being the best quality.
AVAGE	Average age of household members whose main economic activity is farming.
PRIND	A price index computed as the weighted[17] average of the output prices.

Table 2 gives some descriptive statistics of the variables.

Table 2: Descriptive Statistics

Variable	Range	Mean	Std. Deviation
Y	202.20 - 5326.75	1498.67	1101.92
A	0.06 - 11.00	1.38	1.08
L	8.00 - 744.00	124.85	135.27
OX	0 - 5	0.95	1.12
F	0.00 - 500.00	79.91	91.78
LQ	1 - 3	1.55	0.60
AVAGE	17.50 - 64.00	31.32	8.57

5. Estimation and the Results

5.1 Estimation

The production function that we estimated is:

$$\ln\left({y_i}/{PRIND} \right) = \beta_0 + \beta_A \ln(A_i) + \beta_L \ln(L_i) + \beta_F \ln(F_i) + \beta_{ox} \ln(OX_i) + \beta_{LQ} LQ_i + \beta_{AVAGE} \ln(AVAGE_i) + \beta_6 REG3 + \beta_7 REG9 + v_i - u_i \qquad [10]$$

Where REG3 and REG9 are dummies for Region 3 and 9. The other variables are as described in section IV.

We note that for some of the independent variables (F and OX) we had some zero values. To allow for this we added 1 to these variables before transforming them into logarithms.

A priori we expected that Labor, Oxen and Fertilizer should be endogenous variables. This would lead to biased estimates of the coefficients of the model. To correct for this problem we used a two stage procedure. In the first stage we obtained predicted values of the endogenous variables by regressing them on the exogenous variables in the system.[18] We used an omitted-variable test to test for endogeneity of the three variables. Results suggest that while Fertilizer is endogenous, we can reject the hypothesis that Labor and Oxen are endogenous. Consequently, we proceeded treating only Fertilizer as endogenous, and used the predicted value of this variable in the final estimation, i.e. the second stage.

The ML estimates are given in Table 3. We note that we present the t-ratios obtained by using the heteroscedastically consistent covariance matrix. The difference to the standard covariance matrix is only small. We nevertheless conducted a more formal analysis of heteroscedasticity. First, we conducted a White test[19] and the test statistic is calculated as $N^*R^2 = 33.964$ (N is the number of observations). The critical value of the Chi-square with 26 degrees of freedom is 38.89 at the 95% level so we can accept the null hypothesis of homscedasticity. We further conducted a variable by variable analysis. This consisted of testing the significance of the coefficients in the following relationships:

$$\mathrm{var}(e_i) = \sigma^2(\alpha * z)^2 \qquad [11]$$

$$\mathrm{var}(e_i) = \sigma^2 e^{\alpha * z} \qquad [12]$$

where z represents A, L, F, OX, LQ and AVAGE, which are in turn substituted into the expressions. We did not find a significant relationship in any case.

Table 3: MLE Estimates of the Cobb-Douglas, Stochastic Frontier Production Function

Variable	Coefficient	T-ratios Absolute Values
CONSTANT	7.3684	17.884*
ln(A)	0.4289	7.152*
ln(L)	0.0757	2.263**
ln(F+1)	0.1241	4.175*
ln(OX+1)	0.0742	1.367
LQ	-0.1073	2.030**
ln(AVAGE)	-0.2270	2.089**
REG3	-0.3408	4.286*
REG9	-1.3456	8.870*
σ^2	0.2986	4.055*
λ	1.1880	2.284**

Value of log-likelihood:-144.10;Value of restricted log-likelihood:-309.30;
Chi-square based on LR test: 330.40
* and ** denote statistical significance at 1 and 5 % levels respectively

The relatively strong response of output to fertilizer use is an interesting result. It has largest effect of all the variable inputs, and contributes most to R^2 after the land variable. We calculated an elasticity of output with respect to land quality of 17% (evaluated at the mean LQ). This implies quite large gains in output for increments to land quality. For example, a farmer who has land with mean quality 1.55 and who manages to gain access to land of mean quality 2 would be able to obtain a 5% increase in output. Further, we noted that the age structure, of those whose main activity is farming, affects the productivity of the household. The main effect of including AVAGE is on the constant term, as well as a less pronounced effect on L. The regional effects are clearly very important and also very large. Particularly, Daramalo has a substantially lower intercept than other sites. The value of λ indicates that neither disturbance is dominating the error term.

5.2 The Technical Efficiency Scores

We used the result in equation (8) to obtain an estimate of the measure of technical efficiency. The frequency distribution, the range and the average level of technical efficiency is given in Table 4. All figures are in percentages, i.e. the average TE is 72% which means that farmers are, on average, operating 28% below the frontier. The results in Table 4 show that the vast majority of farmers are between 60 and 90 percent efficient. It is clear that, although relatively few farmers fall below 60% TE, large gains in output could be obtained by increasing TE. For most farmers farm output is the main source of income. Hence, for instance, a 40 to 10% increase in output would have substantial welfare gains. For example, the average income from cereals in our sample is 1498.67 Birr. A 28% increase would imply approximately 420 Birr more income from the sale of crops, with the same input levels.

Table 4: Technical Efficiency, Frequency, Range and Mean

Frequency Range	Number of Observations
30-39%	1
40-49%	8
50-59%	24
60-69%	51
70-79%	103
80-89%	61
90-100%	1
Range	32-92%
Average TE	72%

5.3 Determinants of Technical Efficiency

While identifying a large shortfall in potential output is interesting in itself, for policy purposes it is crucial to isolate some of the determinants of TE. For this reson we use the estimated technical efficiency index as the dependent variable in the second stage regression. Annex 1 gives a description of the variables we used in this part of the analysis.[20]

The variables are selected to capture various effects: i) Household characteristics and assets; ii) Acts of nature that may affect farm performance; iii) Market participation; iv) Sharecropping; and v) Access to credit.

To start with, we considered the simple correlation coefficients between the variables listed above and our index of TE. These correlation coefficients and their level of significance are given in Table 5. Only those significant at least at the 10% level are listed. None of these variables show a strong correlation with TE. It is noteworthy that the three strongest effects are due to market participation, plough ownership and sharecropping. The latter has a positive correlation coefficient that might be considered a surprising result.

Table 5: Simple Correlation Coefficients Between TE and Some Determinants

Variable	Correlation Coefficient	Significance Level
PLOUGH	0.150	0.009
OFY	-0.095	0.069
MAACT	0.194	0.001
LABH	0.097	0.064
WS	-0.114	0.036
OXTIM	-0.128	0.022
FRASHLA	0.144	0.011

See Annex 1 for the definition of variables

We then, regressed our TE index on these variables using a censored regression technique, i.e., a tobit model. This procedure is appropriate as the TE index has upper and lower bounds of 1 and 0, respectively. Dropping (step-wise) those variables with a t-ratio of less than 1 we arrived at the final results given in Table 6. We find that household assets, participation in the output market, sharecropping, and a dummy for lazy and careless farmers are the only factors that come out as statistically significant.

Table 6: Censored Regression Estimates of Determinants of Technical Efficiency

Variable	Coefficient	t-ratio
CONSTANT	0.6768	40.377*
WS	-0.0155	-1.232
LN(PLOUGH)	0.0391	2.428**
MAACT	0.0343	2.246**
FRASHLA	0.0468	1.979**
DU220	-0.0613	-2.936**

Sharecroppers (63 in total) had a mean cultivated land area of 1.68 hectare as compared to 1.28 for the rest (a difference significant at the 1% level). The average number of oxen and bulls owned is the same (0.97 for sharecroppers to 0.95 for non-sharecroppers) as is the average number of ploughs owned (1.08 to 1.17). However, sharecroppers have smaller number of family members (5.81 to 6.95: significant at the 5% level). On the input side, we found that sharecroppers use substantially more fertilizer per hectare (70.80 as compared to 54.82 Kg/Ha for the overall average: significant at the 5% level) but also substantially less labor per hectare for weeding (31.1 to 63.1: significant at the 1% level). There is no difference in the amount of labor per hectare for ploughing and harvesting for the two groups.

Some information may also be obtained by comparing the 20% least efficient farmers to the 20% most efficient farmers. As indicated in Table 7 below only Fertilizer per hectare, the number of ploughs and the fraction of total land that is sharecropped had statistically significant different mean values in the two groups. We note that the average area of land cultivated and the average number of oxen and bulls owned is practically the same in the two groups. We also looked at the share cropping and non-share cropping farmers in the top 20 group. Here we found that sharecroppers had fewer persons per household and used more fertilizer per hectare (non-sharecroppers using about the average fertilizer per hectare). Moreover, non-sharecroppers use more labor for ploughing (68 to 36), weeding (70 to 23) and harvesting (67 to 36) (in all cases per hectare). Sharecroppers have a 20% chance of not obtaining oxen at the right time, while non-sharecroppers have a 50% chance. We note that no sharecroppers obtain any income from off-farm activity, which is not the case for non-sharecroppers.

Table 7: Comparison of Group Means: Top 20% to Bottom 20% Technically Efficient Farmers

Variable	Bottom 20%	Top 20%	t-value
F/A	39.27	63.79	3.19*
PLOUG	0.82	1.38	3.20*
FRASHLA	0.082	0.241	2.53**

To look at the problem from another angle we compared the sharecroppers that are in the top 30% efficient group to those that are in the bottom 30% efficient group. The only significant difference between these two groups appears to be fertilizer per hectare (80.05 to 50.41). Fertilizer is clearly not used uniformly and is used more intensively by the sharecroppers. Indeed 12 of the 63 sharecroppers use no fertilizer.

It seems arguable that factor endowments do not determine a family's access to land. Some sharecroppers are more efficient on average but this cannot be a general explanation of access to land either. In the top 20 group they do not reach the highest value of output per hectare. Indeed sharecroppers in the top 20 obtain 1661 Birr per hectare on average, while non-sharecroppers in this group obtain 2372 Birr per hectare (a difference significant at the 5% level). While their technical efficiency scores are very similar their average yields per hectare are not. Further, most sharecroppers fall outside of the top 20 group (two thirds, with 15% of them in the bottom 20 group). What the evidence suggests is that sharecroppers are a fairly heterogeneous group in terms of efficiency and input levels. It would seem useful, but beyond the scope of this article, to look into: i) the landlord tenant relationship, and; ii) the position of the tenant in the village, i.e., looking for wealth and power as possible explanatory variable. We also note that sharecroppers from the different sites also have different efficiency scores (see Table 9). Clearly a more disaggregated analysis is necessary to capture the intra-site differences in sharecropping contracts and perhaps the social structure.

Table 8: Technical Efficiency Scores (in percent) for Share croppers and Non-Share Croppers by Site

Site (Region)	TE score on non-Sharecroppers	TE scores of Sharecroppers (number)
Yetmen (3)	72	75(24)
Shashemene (4)	72	76(26)
Daramalo (9)	73	69(5)
Kersa (4)	73	69(2)
Adaa (4)	72	76(6)

Finally, we give some groupings of the two categories relative to the dummy variables. Table 9 shows that the differences in efficiency between the two groups are not attributable to natural environment variables as captured by RAIN, DURHA, WS, FW, BOA, etc. Nor is access to credit any different in the two groups (very low in either case). Important factors appear to be access to land (DUSCR), oxen (OXTIM), and whether the farmers participate in the market (MAACT) and whether the farmer or family members were too ill to work at an important time (ILL). The level of education of the head of the household (EDHHH) does not appear to be significant.

The coefficient obtained for the variable OXTIM shows that the oxen market is not well developed and that timely and adequate use may hinge on the household being adequately endowed with these factors in the first place. If not, output will suffer. MAACT suggests that those farmers that are more integrated into the market are also more efficient. 195 farmers out of the 249 did operate in the market. It is possible that this variable captures the relative wealth of the two groups, with farmers not operating in the market being in the poorer section.[21] We note that another explanation is that MAACT might be a proxy for access to market, i.e., access to transport and roads.

Table 9: Comparison of Top 20% to Bottom 20% by Various Categories

Variable	Percent of Bottom 20% Falling into Dummy=0 Category	Percent of Top 20% Falling into Dummy=1 Category
DUFEHHH	8	4
DUALP	24	26
EDHHH	14	10
DUOX	24	28
RAIN	16	11
DURHA	34	36
WS	50	40
FW	16	26
BOA	48	44
WDAM	26	26
OXHM	66	38
LAHM	22	18
ILL	32	16
LOAN1	2	0
LOAN2	10	10
LOAN3	6	2
LOAN4	0	0
MAACT	60	84
DUSCR	18	40

6. CONCLUSION

In this paper we estimated a production function for cereal producing farmers in three regions of Ethiopia. Our results show that land-quality and the average age of household members engaged in agriculture are important variables in explaining output variation among farmers. Further regional differences are large and highly significant.

We found that the average level of technical efficiency was only 72%, i.e., that output could be 28% higher with the same level of inputs. Only one farm achieved more than 90% TE. Clearly the output gains by improving efficiency and without additional inputs are very large indeed. The welfare implications for farmers are likewise very high (we compute a gain of 420 Birr at the average value of cereal output, given a 28% increase in TE).

With regard to causes of technical efficiency, we noted that sharecroppers are, on average, more efficient. However, within the group of sharecroppers there is much variation and more detailed study of this problem is required to shed light on this finding. Market integration, as measured by market participation is also positively correlated with technical efficiency. We note that this variable may capture the relative poverty of the farmers as well as the distance from the market. Finally, some of the variations in efficiency are explained by work effort. About 9% of the farmers are classified by their peers as lazy and they are 6% less technically efficient than the average.

NOTES

1 . We use TE and TI as abbreviations for technical efficiency and technical inefficiency respectively.

2 . We assumed that there are no exogenous shocks, or if there are, they affect both farmers in the same way. That is, we rule out luck as accounting for output differences.

3 . Especially in situations where imposing a particular functional form may be inappropriate a bibliography on the topic of efficiency (technical, allocative and some related topics) is available from the authors on request.

4 . We multiply the efficiency score by 100 and get a percentage measure of TE.

5 . This method was developed by Richmond (1974) and is termed as Corrected Ordinary Least Squares (COLS). The distributional assumptions obviously affect the results.

6 . See Greene (1980b) for a discussion.

7 . It is of course possible that more than one farm is technically efficient.

8 . The bounded range on the dependent variable problem does not occur with stochastic frontiers and hence a greater range of distributional assumptions may be used.

9 . Albeit an inconsistent estimate.

10 .Both available from Andre Croppenstedt.

11 . The greater flexibility of the Translog production function would add much to the analysis. However, for smaller data sets, one often (and we did) have a problem with multi collinearity (which may generate insignificant t-ratios and/or wrong signs on the coefficients). One solution to this problem, which is generally termed as a data problem is to increase the data size, whenever possible. Results by Huang and Bagi (1989) have shown that a more flexible functional form will generate lower (slightly) estimates of technical efficiency.

12 . The main advantage of COLS is low computational cost. However, with modern econometrics packages, such as GAUSS or LIMDEP, either problem is easy to compute.

13 . The exponential and the gamma distributions have also been used. As the latter is rather complex to implement, it has hardly ever been used. The fact that we have no good reason for choosing one distributional assumption over the other is a shortcoming of estimating technical efficiency using cross-sectional data.

14 . Teff (White and Black and Mixed Teff), Barely, Wheat, Maize, Millet and Sorghum.

15 . We are grateful to the Department of Economics at the Addis Ababa University for making the data available to us. The data were collected by the Department of Economics in collaboration with the Centre for the Study of African Economies at Oxford University. Funding was provided by SIDA.

16 . We in particular selected only those households who cultivate some land under cereals and deleted missing values and some extreme values for some of the variables.

17 . The weights being the relative proportions of the various cereals in the total value of output.composition.

18 . We used a variety of variables to obtain a good prediction of Labor, Oxen and Fertilizer. In particular, we used the number of ploughs owned, education of the head of the household, age of head of the household, average age of household members, five age groups for both male and female household members, the material of the walls and of the roof of the home, local rainfall, the price index, information on whether the head and the members could read or write, the time taken to collect fuel wood and water, and the exogenous variables in the equation.

19 . By regressing the square of the residual on the regressors, their squares and their cross-products (not including REG3 and REG9).

20 . We are grateful to Phillip Bevan who made her wealth codes available to us. This is a classification of farmers into 15 wealth related categories (and then into many sub-categories) by their peers. The data is large and for our purposes we only concentrated on a few sub-categories: drunkenness and chat addiction; farmers considered lazy or careless; very hard workers; innovative; good farmer; good manager. We note that for the last three categories, we had very few observations (between 0 and 5) and we used only the resulting proxies for the first three categories.

21 . We found a strong correlation between MAACT and the value of stored food (which we used as a proxy for wealth).

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Annex 1:-Description of variables that determine Technical Efficiency

BOA	Dummy if damage to crops due to birds and other animals, 1 if yes.
DU220	Dummy if a farmer is classified as lazy by peers, 1 if yes.
DU226	Dummy if a farmer is considered drunkard, or chat chewer by his peers, 1 if yes.
DU240	Dummy if a farmer is considered to be very hard worker by his peers, 1 if yes.
DUALP	Dummy if a farmer has the adult literacy certificate, 1 if yes.
DUFHH	Dummy for female headed households, 1 if yes.
DUOX	Dummy for farmer having at least two oxen, 1 if yes.
DURHA	Dummy if there was rain at harvest time, 1 if yes.
DUSCR	Dummy for sharecropping, 1 if yes.
EDHHH	Dummy for level of education of household head, 1 if the household head has completed primary school or more.
FRASHLA	Fraction of land cultivated which is sharecropped.
FW	Dummy if damage to crops due to flooding or water logging, 1 if yes.
ILL	Dummy if a farmer or household members too ill to work at an important time, 1 if yes.
LABH	Person days used for harvesting.
LATIM	Dummy if a farmer could not obtain labor at the right time, 1 if yes.
LOAN1	Dummy if a farmer got loan to buy farm or other implements, 1 if yes.
LOAN2	Dummy if a farmer got loan to buy inputs such as seeds, fertilizer or pesticides, 1 if yes.
LOAN3	Dummy if a farmer got loan to buy livestock, 1 if yes.
LOAN4	Dummy if a farmer got loan to pay for hired labor, 1 if yes.
MAACT	Dummy if a household sold some of crop in the market, 1 if yes.
OFY	Off-farm income.
OXTIM	Dummy if a farmer could not obtain oxen at the right time, 1 if yes.
PLOUGH	Number of Ploughs owned by the household.
RAIN	Dummy for rain at good time for the farmer, 1 if yes.
WDAM	Dummy if damage to crops is due to weed, 1 if yes.
WS	Dummy if damage due to wind and storm, 1 if yes.