THE DETERMINANTS OF FARM-LEVEL TECHNICAL EFFICIENCY AMONG ADOPTERS OF IMPROVED MAIZE PRODUCTION TECHNOLOGY IN WESTERN ETHIOPIA[1]

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Abstract

A translog stochastic production frontier was used to analyse the technical efficiency of small farmers using improved maize production technology in Western Ethiopia. The study estimated a mean technical efficiency for the entire sample of 76%, indicating that a significant potential for gains from efficiency improvement in maize production remains to be exploited even among users of improved technology. The study also revealed that farm size, education, access to credit and timely availability of modern inputs are important determinants of technical efficiency among maize producers in Ethiopia. Policies and strategies that promote rural education, credit, timely availability of inputs through better infrastructure and markets will be greatly instrumental in realising considerable gains in maize production with available farm resources through more efficient and appropriate use of improved technology.

1. INTRODUCTION

The growing food gap in Ethiopia has always been attributed to the poor performance of the agricultural sector. In an effort to boost agricultural productivity, policy makers have placed substantial emphasis on new technologies and their adoption by farmers. This effort was coupled with a policy reform programme to reduce the taxation of agriculture, to liberalise markets and to devalue the currency (Techane & Mulat, 1999). The aim was to attain food self-sufficiency through increased use of improved agricultural production technologies, and to allow private sector participation and expansion of the extension services.

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Whilst various incentives have been used to induce farmers to achieve a high rate of adoption of the chosen modern technologies (use of fertilizer, improved seeds, and chemical inputs), little has been achieved in terms of appropriate application and more efficient use of farmers' limited resources. This is mainly attributed to the wrong hypothesis that farmers may not be able to select appropriate technologies but can nevertheless operate technology efficiently when chosen for them. As a result, the field-level performance of the new technologies has been low. The yield levels of major cereal crops has remained too low to justify the substantial investments in the modern inputs used. Mulat (1999) argued that cereal yield increased by only 0.3 percent per annum between 1990 and 1997, and there is no indication that yields have significantly improved since 1994, in spite of the sharp increase in the use of fertilizer and other inputs.

In a dynamic technological and policy environment, it is believed that farmers encounter considerable inefficiencies before realising the intended gains from technological progress. In other words, there is a lag between farmers' attempt to adjust their production decisions to keep pace with changes in the economic environment and achieving the ultimate efficient use of their resources. Ali & Byerlee (1991) pointed out that agriculture in much of the third world has experienced profound changes and can no longer be classified as traditional. In this new situation, the scope for inefficiencies in resource use is much greater and hence development strategies may need to be re-examined.

New technologies demand a new set of skills and knowledge if their productivity-enhancing potentials are to be fully exploited. Deviations of farmers' practices from technical recommendations, coupled with system constraints, will ultimately lead to technical inefficiencies. Knowledge of the extent of such inefficiencies and the underlying farm-level as well as system-level constraints will help guide policy makers to increase agricultural production by enhancing technical efficiency in using improved technologies and farm resources.

We are unaware of any research providing information on empirical measures of the extent of farm-level inefficiencies and associated determinants under improved technology use in Ethiopia. The purpose of this study is, therefore, to quantify farm-specific technical efficiency and identify its determinants among small-scale improved maize producers adopting improved technologies in the Bako area of Western Ethiopia. The selection of maize is based on its importance, more than any other crop, in terms of production, area coverage and better availability and utilisation of improved production technologies (CSA, 1997). The next section gives a brief review of previous

studies addressing this aspect in Ethiopian agriculture and presents the analytical framework. Section 3 describes sources of the data and empirical procedures. Section 4 discusses the empirical results, with conclusions and policy implications distilled in the last section.

2. THE ANALYTICAL FRAMEWORK

Early works on the efficiency of Ethiopian agriculture ranged from those that applied partial measures such as yield per hectare and output per unit of labour to those that apply traditional response functions and programming methods. Only recently have some attempts been made to measure farm efficiency using the new frontier approaches (see Assefa & Heidhues, 1996; Getachew, 1995; Getu *et al.*, 1998; Corppenstedt & Abbi, 1996; Mulat, 1989; Seyoum *et al.*, 1998). However, these studies addressed the technical efficiency of food crop production under traditional technology and lacked methodological rigour to the extent that they ignored the heterogeneity of farmers in terms of the production technologies used. This study attempts to investigate the technical efficiency of a sample of improved maize producers in a stochastic frontier framework.

A method of measuring the productive efficiency of a farm relative to other farms was first suggested by Farrell (1957) using a production frontier. A production frontier is specified to represent the maximum output for a given set of inputs and existing production technology. Failure to attain the frontier output implies the existence of technical inefficiency. Farrell's proposed methodology was, however, deterministic, attributing all deviations from this "best practice" level of production to inefficiency. Aigner *et al.* (1977) and Meeusen & Van den Broeck (1977) independently proposed the stochastic frontier production function to account for the presence of measurement errors and other noise in the data, which are beyond the control of firms.

The stochastic frontier production function is given by:

$$Y_i = F\left(X_i;\beta\right)\exp\left(V_i - U_i\right) \qquad \textbf{(1)}$$

Where Y_i is the quantity of agricultural output of the i^{th} farmer ($i = 1,2,3,...,N$), X_i is a vector of the input quantities, β is a vector of parameters, and $F\left(X_i;\beta\right)$ is a suitable production function, V_i is a random error associated with random factors (e.g. measurement errors in production, weather, luck, etc.). The random errors, V_i, $i = 1,2,3,...,N$, are assumed to be independently and identically distributed as $\mathrm{N}(0,\sigma^2_v)$ random variables, independent of the U_i's, which reflect technical inefficiency in production and are assumed to be

independently and identically distributed as half-normal, $u \sim |N(0, \sigma^2 u)|$. Jondrow *et al.* (1982) suggested a technique for predicting firm-specific technical efficiency using the conditional distribution of U_i given the total disturbance ε_i as:

$$E(u_i/\varepsilon_i) = \frac{\sigma_u \sigma_v}{\sigma}\left[\frac{f(.)}{1-F(.)} - \frac{\varepsilon_i}{\sigma}\left(\frac{\gamma}{1-\gamma}\right)^{0.5}\right] \quad \textbf{(2)}$$

where $\varepsilon_i = V_i - U_i$ and $f(.)$ and $F(.)$ represent, respectively, the density and cumulative distribution functions and σ_u and σ_v are, respectively, the standard errors of U_i and V_i. The maximum likelihood estimation[1] of equation (1) yields estimators for β and γ where $\gamma = \frac{\sigma_u^2}{\sigma_v^2}$ and $\sigma^2 = \sigma^2 u + \sigma^2 v$. γ explains the total variation of output from the frontier which can be attributed to technical inefficiency and lies between zero and one.

Battese & Coelli (1995) proposed a model in which the technical inefficiency effects in a stochastic production frontier are a function of other explanatory variables. In their model the technical inefficiency effect for the i^{th} farmer, U_i, is obtained by truncation (at zero) of the normal distribution with mean, μ_i, and variance σ^2_u, such that

$$\mu_i = Z_i \delta \quad \textbf{(3)}$$

where Z_i is a vector of farm-specific explanatory variables, and δ is a vector of unknown coefficients of the farm-specific inefficiency variables. In this study, we apply the Battese & Coelli (1995) model to estimate the efficiency scores and to identify the socio-economic and institutional factors influencing technical efficiencies of maize producers.

3. DATA AND EMPIRICAL PROCEDURES

Detailed farm-level production data for the 1999/2000 agricultural year collected through intensive year-round surveys by the Ethiopian Rural Households Survey (ERHHS) were used for this study. ERHHS is conducted by the Department of Economics of the Addis Ababa University, Ethiopia in collaboration with USAID. Specifically, this study used the data collected from a sample of 60 farmers in the Bako area in Western Ethiopia who produced maize using fertilizer and improved seed.

For the investigation of the farm-specific technical efficiencies of improved maize producers, the following translog stochastic frontier production function[2] was estimated:

$$\ln Y_i = \beta_0 + \sum_{k=1}^{4} \beta_k \ln(X_{ki}) + \frac{1}{2}\sum_{k=1}^{4}\sum_{j=1}^{4} \beta_{kj} \ln(X_{ki}) \ln(X_{ji}) + V_i - U_i \quad \textbf{(4)}$$

where Y_i denotes total maize output of the i^{th} farmer in kg and $X_k, k = j = 1,2,3,4,$ are the four input variables included (*Land* measured as total area planted to maize in hectare; *labour,* for total pre-harvest family labour, exchange labour, and hired labour used in man-days; *fertilizer,* as the total quantity of fertilizer used in kg; and *oxen,* the number of oxen available to the household[3]. The V_i's are the random variables associated with disturbances in production, and the U_i's are non-negative random variables associated with technical inefficiency of the i^{th} farmer and are obtained by truncation (at zero) of the normal distribution with mean, μ_i, and variance σ_u^2, such that:

$$\mu_i = \delta_0 + \sum_{m=1}^{9} \delta_i X_{mi} \quad \textbf{(5)}$$

where δ_i is a vector of the parameters of the inefficiency model to be estimated, and the X_m's, m =1,2,…,9, are the farm-specific socio-economic variables as well as the institutional factors hypothesized to influence efficiency of resource use under improved maize technology in Western Ethiopia. These are: *farm size* measured as land planted to maize in hectares; age of the household head in years; *extension* visits paid to the farmer; *distance* of the nearest product/input market from home in minutes and five dichotomous (0-1) dummy variables accounting for *credit* for modern inputs, *education*/literacy of the head of household, *timely availability* of inputs (0-1), *plot ownership* (0-1) based on whether the maize plot was allocated by local administration and thus belonged to the farmer, and *plot quality* (0-1) based on whether the maize plot was perceived as fertile by the farmer.

In the translog frontier, the elasticity of the mean output with respect to land is also a function of the technical inefficiency effects because the model for the technical inefficiency effects is a function of land, as specified in equation (5). In general, the elasticities of mean output with respect to each of the inputs are defined by:

$$\frac{\partial \ln E(Y)}{\partial \ln X_k} = \beta_k + \beta_{kk}\overline{\ln X_k} + \sum_{j=1\neq k}^{k} \beta_{kj}\overline{\ln X_{kj}} - \theta_i\left(\frac{\partial \mu_i}{\partial X_{ki}}\right), k = 1,2,3,4. \quad \textbf{(6)}$$

where μ_i is defined by equation (5) and θ_i is defined by

$$\theta_i = 1 - \frac{1}{\sigma}\left\{\frac{\phi\left(\frac{\mu_i}{\sigma} - \sigma\right)}{\Phi\left(\frac{\mu_i}{\sigma} - \sigma\right)} - \frac{\phi\left(\frac{\mu_i}{\sigma}\right)}{\Phi\left(\frac{\mu_i}{\sigma}\right)}\right\} \quad \textbf{(7)}$$

where ϕ and Φ represent the density and distribution functions of the standard normal random variable, respectively. The last term in equation (6) drops out for all variables except land as it also appears in the inefficiency effects model. Significance tests on the estimated elasticities are easily conducted by recovering their standard errors from the standard errors of the estimated parameters of the translog frontier production function and the averages of the logs of inputs (see Greene, 2000, for derivations).

Moreover, tests of hypotheses involving the parameters of the stochastic frontier and inefficiency model are conducted using the generalised Likelihood Ratio (LR) statistic, λ , defined by:

$$\lambda = -2 \ln [L(H_0)/L(H_1)] \quad \textbf{(8)}$$

where $L(H_0)$ is the value of the likelihood function for the frontier model, in which the parameter restrictions specified by the null hypothesis, H_0, are imposed; and $L(H_1)$ is the value of the likelihood function for the general frontier model. If the null hypothesis is true, then λ has approximately a chi-square (or mixed chi-square) distribution with degrees of freedom equal to the difference between the number of parameters estimated under the null and alternative hypotheses (Coelli & Batesse, 1996).

4. EMPIRICAL RESULTS

4.1 Parameter estimates and tests of hypotheses

The maximum-likelihood estimates of the parameters of the translog stochastic frontier production function specified in equation (4) and the inefficiency model specified in equation (5) were obtained using the computer program FRONTIER 4.1 (Coelli, 1994). These results, together with the output elasticities of inputs, are presented in Table 1.

The elasticities of mean output were estimated at the means of the input variables and the explanatory variables in the inefficiency model using equations (6) and (7). The output elasticities of land, fertilizer and oxen are positive and significant as expected.

Table 1: Maximum-likelihood estimates of the parameters of the translog stochastic frontier and inefficiency model for maize producers in Western Ethiopia [a,b]

Variable	Parameter	ML estimates	Elasticities
Stochastic frontier			
Intercept	β_0	9.382*** (4.23)	-
ln (land)	β_1	0.632 (1.58)	0.54 **(2.13)
ln (labour)	β_2	-1.512 (-1.19)	-0.09* (1.91)
ln (fertilizer)	β_3	0.46* (1.87)	0.41**(2.05)
ln (oxen)	β_4	-0.38 (-1.18)	0.24*(1.87)
½ [ln(land)]^2	β_{11}	0.02*** (4.67)	
½ [ln(labour)]^2	β_{22}	0.90* (1.85)	
½ [ln(fertilizer)]^2	β_{33}	0.02 1(0.12)	
½ [ln(oxen)]^2	β_{44}	0.092** (2.01)	
ln (land)*ln (labour)	β_{12}	-0.372 (-1.14)	
ln (land)*ln (fertilizer)	β_{13}	0.261 (1.43)	
ln (land)*ln (oxen)	β_{14}	-0.501***(-5.39)	
ln (labour)*ln (fertilizer)	β_{23}	-0.091* (-1.98)	
ln (labour)*ln (oxen)	β_{24}	0.182(1.22)	
ln (fertilizer)* ln (oxen)	β_{34}	-0.021 (-0.23)	
Inefficiency model			
Intercept	δ_0	0.246 (0.32)	
Farm size	δ_1	-0.05** (-2.66)	
Age	δ_2	-0.01 (-1.38)	
Credit	δ_3	-1.271* (-1.76)	
Education	δ_4	-1.49*** (-3.75)	
Extension	δ_5	0.01 (0.08)	
Timely availability of inputs	δ_6	-1.51** (2.37)	
Plot ownership	δ_7	-0.5* (-1.67)	
Market distance	δ_8	0.01 (1.44)	
Plot quality	δ_9	-0.28 (-1.11)	
γ		0.982*** (260)	
σ_v^2		0.313*** (5.3)	
Log likelihood		13.60	

[a] ***, significant at 0.01 level; **, significant at 0.05 level; *, significant at 0.1 level.
[b] The numbers in parentheses represent asymptotic t-ratios, correct to two significant digits.

As shown in Table 1, these estimates are 0.54, 0.41, and 0.24 for land, fertilizer and oxen respectively. The results confirm that these are critical

inputs in maize production. Unexpectedly, the output elasticity of labour turned out to be negative but not significant at less than 10 percent probability level. An examination of the labour data revealed that there was actually excess utilisation of labour on most maize farms as indicated by the average labour use of 45 man-days per hectare as opposed to the 20 man-days average labour use per hectare of improved maize within the SG 2000 Project (see Seyoum *et al.*, 1998).

The choice of the empirical frontier production function was made based on the generalised LR test specified in equation (8) without having to impose any functional form a priori. Further, other tests of the hypothesis involving the parameters of the frontier and inefficiency model are conducted using the same procedure. The test results are presented in Table 2.

Table 2: Generalised LR tests of hypotheses involving the parameters of the stochastic frontier and inefficiency model for improved maize producers in Western Ethiopia

Null Hypothesis	Test statistic (λ)	χ^2 - Critical value	Decision
H_0: $\beta_{kj}=0$	24.67	16.92	Reject H_0
H_0: $\gamma=0$	9.35	7.05*	Reject H_0
H_0: $\gamma=\delta_0=\delta_1=\delta_2=\ldots=\delta_9=0$	26.27	19.05*	Reject H_0
H_0: $\delta_1=\delta_2=\ldots=\delta_9=0$	23.12	16.92	Reject H_0

* The (mixed) χ^2 critical values for the hypotheses involving $\gamma=0$ are obtained from Kodde & Palm (1986)..

The functional form of the stochastic frontier was determined by testing the adequacy of the Cobb-Douglas model against the more flexible translog model. As shown in Table 2, the first null hypothesis specifying that the Cobb-Douglas model is an appropriate representation of the data, given the specifications of the translog, was highly rejected indicating that the Cobb-Douglas is not actually appropriate. Therefore, the translog stochastic frontier model was used in this study.

The second null hypothesis, H_0: $\gamma=0$, specifies that the technical inefficiency effects are not stochastic. Alternatively, it tests whether any frontier model is appropriate at all as opposed to a traditional response function. As this is clearly rejected, the test results confirm that the traditional response function is not an adequate representation for maize production in Western Ethiopia, given the specifications of the translog stochastic frontier and inefficiency model. Furthermore, the third null hypothesis, H_0: $\gamma=\delta_0=\delta_1=\delta_2=\ldots=\delta_9=0$, specifies that both the parameters of the stochastic frontier and the inefficiency model are jointly zero such that the inefficiency effects are absent from the model. The results show that this is again strongly rejected indicating that the stochastic frontier model with the inefficiency effects is the preferred model. The last null hypothesis, H_0: $\delta_1 = \delta_2 = ... = \delta_9 = 0$, specifies that the explanatory variables in the model for the technical inefficiency effects have zero coefficients. This null hypothesis is also strongly rejected implying that, taken together, the explanatory variables have a significant impact on the inefficiency effects.

4.1.1 Determinants of technical efficiency

The estimates of the coefficients for the inefficiency variables are of particular interest in this study. The estimate of the variance parameter, γ, is significantly different from zero, which implies that the inefficiency effects are significant in determining the level and variability of maize output of farmers in Western Ethiopia. The traditional (average) production function with no technical inefficiency effects is thus not an adequate representation of the data. As shown in Table 1, the coefficients for farm size, credit, education, and timely availability of inputs, are negative and significant, suggesting that they significantly and negatively influence inefficiency.

The negative influence of farm size on inefficiency indicates that those farmers who operate relatively large maize plots are less inefficient in maize production under improved technology. These farmers are more likely to exploit the potential of improved varieties and thus make efficient use of their existing farm resources by allocating more land to improved maize. As expected, access to input credit, education, and timely availability of inputs had inefficiency-reducing effect. Assefa (1995) also obtained a positive and significant impact of education, timely input supply, and credit on technical efficiency of crop production in central Ethiopia.

The rest of the variables, including extension, plot quality, plot ownership, and age turned out to be negative and insignificant. Market distance was positive but insignificant and this may indicate that relatively remote farmers are more likely to experience inefficiency arising from poor access to inputs and lack of markets for maize.

Plot ownership has turned out to have an inefficiency-reducing but insignificant effect. This direction of influence is in agreement with Gavian & Ehui (1999) who, based on their study in Arsi region of Ethiopia, found that production efficiency on owned plots was higher than that on contracted plots even though they attributed this variation to plot quality differences and not to a lower intensity of use of inputs like fertilizer and improved seeds. Contrary to these, however, Corppenstedt & Abbi (1996) found that sharecroppers are more technically efficient than owner cultivators in three regions of Ethiopia. The results are, therefore, mixed suggesting a need for further investigation.

4.1.2 Technical efficiency estimates

The frequency distribution of the technical efficiency estimates obtained is given in Table 3. Predicted technical efficiencies ranged between 7% and 98%. The results show that 36% of the sample maize producers have technical efficiencies greater than 90%, operating close to the technology frontier. However, about 47% of the sample maize producers have technical efficiency levels below 80% while the mean technical efficiency of the entire sample was estimated at 76% indicating substantial inefficiencies in maize production under improved technology.

Table 3: Frequency distribution of technical efficiency estimates for a sample of maize producers in Western Ethiopia

Level (%)	Number of farms	% farms	Cumulative %
<50	6	10	10
50 - 60	7	11.7	21.7
61 - 70	7	11.7	33.3
71- 80	8	13.3	46.7
81- 90	10	16.7	63.3
91-100	22	36.7	100
Mean =76 Minimum =7 Maximum =98			

This suggests that by operating at full technical efficiency levels, maize producers can increase their production by an average of 24% with their available farm resources and improved technology.

The study confirmed that maize production under new technology involves considerable inefficiencies in Western Ethiopia. It is argued that new and improved technologies can bring about inefficiency of production and continue until such time that farmers acquire enough technical knowledge and are well integrated into the input and product markets through better information and infrastructure, credit and extension services (Ghatak & Ingersent, 1984). For instance, Xu & Jeffrey (1998) obtained significantly lower technical, allocative, and economic efficiency indices for hybrid rice production in China as compared with conventional rice production across all the three regions studied. On the other hand, Singh *et al.* (2000) obtained lower technical, allocative and economic efficiency for newly established Indian dairy processing plants after liberalisation of the dairy industry compared to the old plants as they needed time to reach full operation, the right choice of products and other managerial skills required for higher performance.

5. CONCLUSION AND POLICY IMPLICATIONS

In this study, the technical efficiency levels of maize producers in Western Ethiopia were estimated and the influence of factors determining technical efficiency were measured using a stochastic frontier production function framework. The mean technical efficiency of the sample maize producers was estimated at 76% indicating that there are substantial inefficiencies in maize production under improved technology in Western Ethiopia. By operating at full technical efficiency levels, maize producers can increase production by an average of 24% with the given inputs and currently available technology.

An examination of the relationship between efficiency and various socio-economic and institutional attributes revealed that farm size, education, provision of input credit, and timely availability of critical inputs like fertilizer, improved seed and chemicals are important factors positively influencing the technical efficiency of maize producers. The results suggest that any attempt to improve the productive efficiency of farmers must give due attention to rural education, provision of credit for critical inputs like fertilizer, improved seeds, and chemicals, and timely supply of modern inputs. Policies and strategies that promote rural education, credit, timely availability of inputs through better infrastructure and markets will be greatly instrumental in realising considerable gains in maize production with available farm resources through more efficient and appropriate use of improved technology.

NOTES

1. *The use of single-equation model in equation (1) is justified by assuming that farmers maximise expected rather than actual profits as is commonly done in studies of this type (Zellner, Kmenta & Dreze, 1966; Kopp & Smith, 1980).*

2. *The Cobb-Douglas frontier production function was highly rejected by the data, given the specifications of the translog stochastic frontier production function.*

3. ***Results obtained from an initial model estimation with an index of seeds and chemicals included were not plausible and, instead, excluding this variable actually improved the results. This is because only few farmers actually used limited amounts of chemicals and that seeding rates were also similar across farmers.***

REFERENCES

AIGNER DJ, LOVELL CAK & SCHMIDT P (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6:21-37.

ALI M & BYERLEE D (1991). Economic efficiency of small farmers in a changing world: A survey of recent evidence. *Journal of International Development* 3(1):1-27.

ASSEFA A (1995). *Analysis of production efficiency and the use of modern technology in crop production: A study of smallholders in the Central Highlands of Ethiopia*. Arbeiten zur Agrarwirschaft in Entwicklungsländern. Wissenschaftsverlag Vauk Kiel, Germany.

ASSEFA A & HEIDHUES F (1996). Estimation of technical efficiency of smallholder farmers in the Central Highlands of Ethiopia. *Ethiopian Journal of Agricultural Economics* 1(1):18-47.

BATTESE G & COELLI TJ (1995). A model of technical efficiency effects in a stochastic frontier function for panel data. *Empirical Economics* 20:325-332.

CSA (Central Statistical Authority) (1997). *Statistical abstract of Ethiopia*. Addis Ababa.

COELLI TJ (1994). *A guide to FRONTIER Version 4.1: A computer program for stochastic frontier production and cost function estimation*. Mimeo, Department of Econometrics, University of New England, Armidale, Australia.

COELLI TJ & BATTESE GE (1996). Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural Economic* 40:103-128.

CORPPENSTEDT A & ABBI M (1996). An analysis of the extent and causes of the technical efficiency of farmers growing cereals in Ethiopia. *Ethiopian Journal of Economics 5*(1):39-62.

FARRELL MJ (1957). The measurement of productive efficiency. *Journal of Royal Statistical Society* Series A, 120:253-290.

GAVIAN S & EHUI S (1999). Measuring the production efficiency of alternative land tenure contracts in a mixed crop-livestock system in Ethiopia. *Agricultural Economics* 20:37-49.

GETACHEW A (1995). *Production efficiency analysis: The case of smallholder farming in the coffee sector of Ethiopia and Kenya*. Farming systems and resource economics in the Tropics, Vol. 23, Wissenschaftsverlag Vauk, Kiel, Germany.

GETU H, STORCK H, BELAY K & VISCHT K (1998). Technical efficiencies of smallholder annual crop production in moisture stress area of Eastern Oromia of Ethiopia: A stochastic frontier analysis. *Ethiopian Journal of Agricultural Economics* 2(2):91-115.

GHATAK S & INGERSENT K (1984). *Agricultural and economic development.* Wheatsheaf Books Ltd, Sussex.

GREENE WH. (2000). *Econometric analysis*. Prentice-Hall, Inc., New York.

JONDROW J, LOVELL K, MATEROV I & SCHMIDT P (1982). On the estimation of technical inefficiency in the stochastic frontier production model. *Journal of Econometrics* 19:223-38.

KODDE DA & PALM FC (1986). Wald criteria for jointly testing equality and inequality restrictions. *Econometrica* 54:1243-1248.

KOPP RJ & SMITH VK (1980). Frontier production function estimates for steam electric generation: A comparative analysis. *Southern Economic Jou*rnal 47:1049-1059.

MEDaC (1999). *Survey of the Ethiopian economy: Review of post-reform developments (1992/93-1997/98).* Ministry of Economic Development and Cooperation (MEDaC).

MEEUSEN W & VAN DEN BROECK J (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18:435-444.

MULAT D (1989). *The production efficiency of food grains producers in Ethiopia: The case of small farms in Arssi Province*. PhD Dissertation, Department of Economics, University of Strathclyde, UK.

MULAT D (1999). *The challenge of increasing food production in Ethiopia*. In: Alemayehu G & Berhanu N (eds.), The Ethiopian economy: performance and evaluation. Proceedings of the Eighth Annual Conference on the Ethiopian economy, Nazareth.

SEYOUM ET, BATTESE GE & FLEMING EM (1998). Technical efficiency and productivity of maize producers in Eastern Ethiopia: A study of farmers within and outside the Sasakawa Global 2000 project. *Agricultural Economics* 19(3):341-348.

SINGH S, COELLI T & FLEMING E (2000). *Measurement of technical, allocative, and economic efficiency in Indian dairy processing plants: an input distance function approach*. CEPA working papers, Department of Econometrics, University of New England, Australia.

TECHANE A & MULAT D (1999). *Institutional reforms and sustainable input supply and distribution in Ethiopia*. In: Workineh N, Legesse D, Abebe H & Solomon B (eds), Institutions for rural development. Proceedings of the 4th Annual Conference of the Agricultural Economics Society of Ethiopia, Addis Ababa.

XU X & JEFFREY SR (1998). Efficiency and technical progress in traditional and modern agriculture: Evidence from rice production in China. *Agricultural Economics* 18:117-165.

ZELLNER A, KMENTA J & DREZE J (1966). Specification and estimation of Cobb-Douglas production function models. *Econometrica* 34:784-795.