CHAPTER 5

EMPIRICAL ANALYSIS OF PRODUCTION EFFICIENCY UNDER TRADITIONAL AND IMPROVED TECHNOLOGY IN EASTERN ETHIOPIA

5.1 Introduction

Many developing countries including Ethiopia have made substantial investments in agricultural research and extension to increase agricultural production through new technologies. Despite considerable technological change since the Green Revolution, however, agricultural production in these countries continued to encounter substantial inefficiencies due to farmers' high unfamiliarity with new technology, poor extension and education services, and poor infrastructure, among others (Ali and Byerlee, 1991; Ghatak and Ingersent, 1984; Xu and Jeffrey, 1998). While there are a considerable number of studies dealing with technical efficiency of farmers in developing countries, very few studies have addressed both technical, allocative and economic efficiencies (Taylor et al., 1986; Bravo-Ureta and Rieger, 1991; Bravo-Ureta and Evenson, 1994; Sharma et al., 1999) employing the stochastic efficiency decomposition technique proposed by Bravo-Ureta and Rieger (1991) which was an extension of the model originally introduced by Kopp and Diewert (1982). However, due to scale biases arising from imposing an input-orientated framework on the output-orientated stochastic production frontier results, the efficiency estimates obtained based on Bravo-Ureta and Rieger's (1991) decomposition methodology either overestimate or underestimate the true measures depending on the returns to scale associated with the production technology and are thus inconsistent. Although a couple of authors (e.g., Singh et al., 2000) recognized the limitation of the conventional efficiency decomposition, no attempt has been made to improve upon the technique. This study, therefore, extends the Bravo-Ureta and Rieger's (1991) efficiency decomposition methodology to account for scale effects.

This chapter analyses the production efficiency of smallholder farmers in eastern Ethiopia. The study employed a robust efficiency decomposition technique, which accounts for scale effects, to analyze the technical, allocative, and economic efficiencies of smallholder farmers under traditional and improved production technologies. Specifically, the extended efficiency decomposition approach is employed to assess the impact of improved maize technologies on the efficiency of maize production in Meta district and the impact of NEP on farmers' overall technical, allocative, and economic efficiency in Babile and Meta districts. Socio-economic and institutional factors influencing farmer efficiency are also analyzed. The next section presents the analytical framework employed to conduct the intended production efficiency analyses. Results of the empirical application of the framework to maize production in Meta are discussed in section 5.3. Empirical analysis of overall farm level production efficiency is presented in section 5.4, and the final section distills conclusions and implications.

5.2 The Analytical Framework

While technical efficiency is the ability to produce a given level of output with a minimum quantity of inputs under certain technology, allocative efficiency refers to the ability of choosing optimal input levels for given factor prices. Productive (or economic) efficiency is the product of technical and allocative efficiency. Since Farrell's seminal paper, there has been a growing interest in methodologies and their applications to efficiency measurement. While early methodologies were based on deterministic models that attribute all deviations from maximum production to inefficiency, the introduction of the stochastic frontier production function has made it possible to separately account for factors beyond and under the control of firms (Aigner et al., 1977; Meeusen and van den Broeck, 1977). The production technology of a firm is represented by a stochastic frontier production function (SFPF) as follows

$$Y_i = f(X_i;\beta) + v_i - u_i, \tag{5.1}$$

where Y_i measures the quantity of agricultural output of the i^{th} firm, X_i is a vector of the input quantities, β is a vector of parameters, and $f(X_i;\beta)$ is the production function; v_i s are assumed to be independently and identically distributed $N(0,\sigma^2{}_v)$ random errors, independent of the u_i s; and the u_i s are non-negative random variables, associated with technical inefficiency in production, and are assumed to be independently and identically distributed as half-normal, $u \sim |N(0,\sigma^2 u)|$. The maximum likelihood estimation of equation (5.1) yields estimators for β and λ where $\lambda = \frac{\sigma_u}{\sigma_v} \geq 0$ and $\sigma^2 = \sigma^2 u + \sigma^2 v$. The assumptions made on the statistical distributions of v and u, mentioned above, make it possible to calculate the conditional mean of u_i given $\varepsilon_i = v_i - u_i$ as

$$E(u_i / \varepsilon_i) = \frac{\sigma_u \sigma_v}{\sigma} \left[\frac{f^*(\varepsilon_i \lambda / \sigma)}{1 - F^*(\varepsilon_i \lambda / \sigma)} - \frac{\varepsilon_i \lambda}{\sigma} \right], \qquad (5.2)$$

where F^* and f^* are, respectively, the standard distribution and the standard normal density functions, evaluated at $e_i \lambda / \sigma$. Therefore, equations (5.1) and (5.2) provide estimates of u and v after replacing ε, σ, and λ by their estimates.

5.2.1 The Stochastic Efficiency Decomposition Methodology

Bravo-Ureta and Rieger (BUR) utilized the level of output of each firm adjusted for statistical noise, observed input ratios, and the parameters of the stochastic frontier production function (SFPF) to decompose overall efficiency into technical and allocative efficiency. The parameters of the SFPF are actually used to derive the parameters of the dual cost function. For example, if v_i is now subtracted from both sides of equation (5.1), we obtain

$$Y_i^* = f(X_i; \beta) - u_i = Y_i - v_i, \qquad (5.3)$$

where Y_i^* is the i^{th} firm's observed output adjusted for the statistical noise captured by v_i, $f(\cdot)$ is the deterministic frontier output, and u and v are, respectively, the inefficiency and random components of overall deviations from the frontier. Adjusted output Y^* is used to derive the technically efficient input vector, X^t. The technically efficient input vector for the i^{th} firm, X_i^t, is derived by simultaneously solving equation (5.1) and the observed input ratios $\frac{x_1}{x_i} = k_i (i > 1)$ where k_i is equal to the observed ratio of the two inputs in the production of Y_i^*. The technically efficient input vectors form the basis for deriving the technical efficiency measures by taking ratios of the vector norms of the efficient and observed input quantities while the adjusted output is used to derive allocative and economic efficiencies employing the dual cost frontier function that is analytically derived from the SFPF.

In the BUR method, the parameters of the frontier function are estimated using an output-orientated approach but technical efficiency is derived by imposing an input-orientated approach implied by the simultaneous solution of adjusted outputs and the observed input ratios to yield the technically efficient input vectors. This is clearly inconsistent and will give technical efficiency estimates that are very different from those obtained from the maximum-likelihood estimation of the SFPF in equation (5.1) which is output-orientated unless the firms are operating under constant returns to scale (CRTS). Even if the hypothesis of constant returns to scale is not rejected, consistent estimates cannot be obtained as long as the function coefficient is numerically different from unity. A positive scale effect indicates operation in an irrational zone of production (i.e., IRTS) whereas a negative scale effect implies a rational production zone (i.e., DRTS).

A variable returns to scale technology (VRTS) will generally give different estimates of technical, allocative, and economic efficiency when the output and input-orientated approaches are used. Under decreasing returns to scale (DRTS), the BUR method underestimates technical, allocative, and economic efficiency (e.g., Bravo-Ureta and Rieger, 1991 for dairy farms in USA; Bravo-Ureta and Evenson, 1994 for cotton production in Paraguay) while it overestimates the corresponding efficiencies under increasing returns to scale (IRTS) (e.g., Bravo-Ureta and Evenson, 1994 for cassava production in Paraguay; Sharma et al., 1999 for swine production in USA).

5.2.2 A Consistent Approach to Efficiency Decomposition

Adopting an input orientation for efficiency decomposition when original specifications have an output orientation requires that observed output be adjusted for statistical noise as well as scale effects. This is accomplished by first defining a scale factor as the deviation from CRTS as

$$\eta_i = \psi - 1, \qquad (5.4)$$

where η_i is the scale factor for the i^{th} firm and ψ is the function coefficient of the production technology. The output-orientated technical inefficiency effect of the i^{th} firm in the composed error structure in equation (5.1) is denoted by u_i. Imposing an input-orientated approach on the SFPF will produce an input-orientated technical inefficiency effect, denoted as u_i^i, that is actually composed of the pure technical inefficiency effect , u_i , and a scale effect, ζ_i, such that

$$u_i^i = u_i + \zeta_i . \tag{5.5}$$

However, consistency requires that $u_i^i = u_i$. To the extent that there is a non-zero scale effect, the conventional decomposition methodology gives inconsistent efficiency estimates. From this it follows that the observed output must be adjusted not only for statistical noise but also for scale effects while employing the input-orientated approach to decompose overall efficiency into technical and allocative efficiency measures based on the (output-orientated) estimates of the SFPF. The scale effect is a proportion of the output-orientated technical inefficiency effect, the factor of proportionality being the scale factor η. Therefore, the scale effect of the i^{th} firm can be given by

$$\zeta_i = \eta_i u_i . \tag{5.6}$$

From equations (5.5) and (5.6), the input-orientated adjusted output of the i^{th} firm is derived and given as

$$Y_i^{i*} \equiv f(X_i;\beta) - u_i^i = Y_i - v_i - \eta_i u_i , \tag{5.7}$$

where Y_i^{i*} is the observed (or actual) output adjusted for statistical noise and scale effects.

Figure 5.1 illustrates the difference between observed and adjusted output in the input and output orientation in the SFPF framework. The technically efficient input quantities obtained by projecting the output-orientated adjusted outputs, Y_k^{o*} and Y_l^{o*}, on the deterministic frontier are typically BUR efficient quantities and are denoted as X_k^B and X_l^B for the k^{th} and l^{th} firms, respectively.

On the other hand, the technically efficient quantities for the k^{th} and l^{th} firms obtained by projecting the input-orientated adjusted outputs, Y_k^{i*} and Y_l^{i*} , on the deterministic frontier are the consistent input vectors, X_k^t and X_l^t, respectively, used in this study as given in equation (5.7). For firm k, operating under DRTS, X_k is the vector of actual input use and Y_k is the actual output. Given the level of input use, the stochastic frontier output is represented by Y_k^s. The total deviation from the deterministic frontier output for this firm (v - u) is the distance $Y_k^d Y_k$. This distance may be decomposed into the random component ($v = Y_k^s Y_k^d$) and the inefficiency component ($u = Y_k^s Y_k$) (Jondrow et al., 1982). As indicated by equation (5.7), u_k (i.e., distance $Y_k^s Y_k$) is subtracted from the deterministic frontier output to obtain the output-orientated adjusted output for firm k, Y_k^{o*}. The input-orientated adjusted output for this firm, Y_k^{i*}, that rationalizes the consistent technically efficient input vector X_k^t, is obtained by making an upward scale adjustment equivalent to the distance Y_k^{i*} Y_k^{o*} to the output orientated adjusted output, Y_k^{o*}, that rationalizes BUR technically efficient input vector X_k^B.

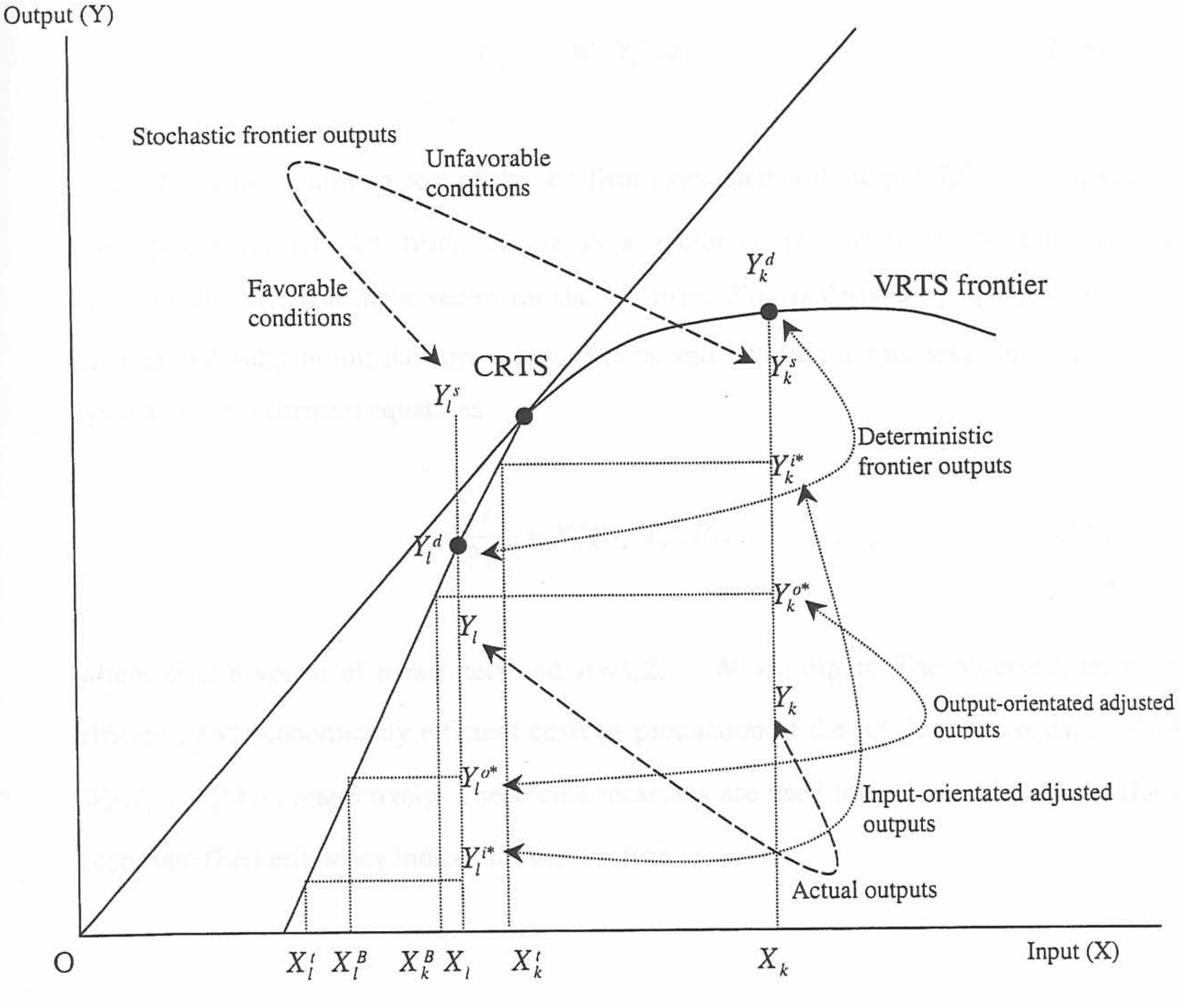

Figure 5.1: The stochastic frontier production function with output and input orientation.

Similarly firm l, operating under IRTS, uses inputs X_l to produce Y_l. Stochastic frontier output for this firm is Y_l^s. The total deviation from the deterministic frontier function, $Y_l^d Y_l$, may be partitioned into the random component $v = Y_l^s Y_l^d$ and the inefficiency component $u = Y_l^s Y_l$. The output-orientated adjusted output of firm l will similarly be $Y_l^{o*} = Y_l^d - Y_l^s Y_l$. The input-orientated adjusted output for this firm, Y_l^{i*}, that rationalizes the consistent technically efficient input vector X_l^t, is obtained by making a downward scale adjustment equivalent to the distance $Y_l^{i*} Y_l^{o*}$ to the output-orientated adjusted output, Y_l^{o*}, that rationalizes BUR technically efficient input vector X_l^B. In figure 5.1, $X_k{}^t$ and X_l^t refer to the consistent technically efficient input vectors for the k^{th} and l^{th} firms, respectively.

Assuming that the production function in equation (5.1) is self-dual (e.g., Cobb-Douglas), the dual cost frontier can be derived algebraically and written in a general form as

$$C_k = C(W_k, Y_k^{i*}; \alpha), \tag{5.8}$$

where C_k is the minimum cost of the k^{th} firm associated with output Y_k^{i*}. W_k is a vector of input prices for the k^{th} firm, and α is a vector of parameters to be estimated. The economically efficient input vector for the k^{th} firm, $X_k{}^e$, is derived by applying Shephard's Lemma and substituting the firm's input prices and adjusted output level into the resulting system of input demand equations

$$\frac{\partial C_k}{\partial W_n} = X_k^e(W_k, Y_k^{i*}; \theta), \tag{5.9}$$

where θ is a vector of parameters and $n = 1, 2, \ldots\ldots, N$ are inputs. The observed, technically efficient, and economically efficient costs of production of the k^{th} firm are equal to $W_k{}'X_k$, $W_k{}'X_k{}^t$, $W_k{}'X_k{}^e$, respectively. These cost measures are used to compute technical (TE) and economic (EE) efficiency indices for the k^{th} firm as

$$\mathrm{TE}_k = \frac{W_k{}' X_k{}^t}{W_k{}' X_k}, \tag{5.10}$$

and

$$\mathrm{EE}_k = \frac{W_k{}' X_k{}^e}{W_k{}' X_k}. \tag{5.11}$$

Following Farrell (1957) the allocative efficiency (AE) index can be derived from equations (5.10) and (5.11) as

$$\mathrm{AE}_k = \frac{W_k{}' X_k{}^e}{W_k{}' X_k{}^t}. \tag{5.12}$$

Following the quantification of the technical, allocative, and economic efficiency measures, a second stage analysis involves a regression of these measures on several hypothesized socio-economic and institutional factors affecting efficiency of farmers. This will help to identify the determinants of technical, allocative, and economic efficiency. Although few authors (e.g., Battese and Coelli, 1995; Kumbhakar, 1994) challenge this approach by arguing that the farm-specific factors should instead be incorporated directly in the first stage estimation of the stochastic frontier, many justify the two-stage method in that the variables can only have a round-about effect on efficiency (Bravo-Ureta and Rieger, 1991; Bravo-Ureta and Evenson, 1994; Sharma et al., 1999). The linear regression model[4] has thus been a common approach to the analysis of the effects of farm-specific factors on productive efficiency. However, because efficiency scores are bounded between zero and one and also cannot be assumed to be normally distributed as they are mostly skewed, transformation of these scores using Box-Cox procedures and taking their logs is important for regression analysis (Judge et al., 1985). A linear regression model of the following form could thus be used for the analysis of the determinants of efficiency (Squires and Tabor, 1991; Assefa, 1995).

$$\ln\left(\mathrm{E}_i / 1 - \mathrm{E}_i\right) = X_i' \beta + \varepsilon_i, \tag{5.13}$$

[4] Censored regression models such as the tobit model could be used but these are less appealing because efficiency scores obtained from stochastic production frontiers are not censored at zero, one, or both and hence there is generally little or no basis for using censored regression as opposed to OLS.

where E_i is the i^{th} firm's level of efficiency, X_i is a vector of explanatory variables, β is a vector of parameters to be estimated, and ε_i are identically and independently distributed random errors $N(0, \sigma^2)$.

5.3 Empirical Analysis of Maize Production Efficiency of Smallholders Under Traditional and Improved Technology

Maize is the most important cereal grain in Ethiopia in terms of production, area coverage and better availability and utilization of new production technologies (CSA, 1997; Mulat, 1999). The maize sector has benefited from relatively better technological change in terms of high-yielding varieties of seeds, fertilizer, chemicals, and post-harvest techniques. The first maize hybrid in the Ethiopian breeding program was BH-140, which was released in 1988 from the Bako Research Center (Kebede, 1993). With subsequent efforts, BH-660 was also released in 1994 by the Bako Research Center and became one of the most successful hybrid varieties. It has a wider adaptability, growing at altitudes ranging from 1650 meters to 2200 meters with annual precipitation of 1000-1500 mm. It needs up to 170 days to maturity and performs better under high rainfall, good soil conditions and high dose of fertilizer. Maize research has yet to develop high-yielding and drought-tolerant varieties for the drought-prone farming zones. The yield potential of BH 660 is well over 100 quintals per hectare (ESE, 1997). The recommended packages for hybrid maize technology are 100 kg per hectare DAP, 100 kg per hectare UREA, 25 kg per hectare seed, and other appropriate cultural practices such as row planting. However, weak capacity in producing and distributing the hybrid seeds and the high risk associated with weather problems have been a major constraint to wider adoption of BH 660.

However, new maize technologies are known to require a new set of skills and knowledge, farmers' integration into the input and product markets, and access to infrastructure, credit and educational services to fully exploit their productivity-enhancing potentials. Mulat (1999) argued, for instance, that the potential to increase yield through improved management practices is not given due attention in Ethiopia. The effort directed towards enhancing the technical skill and management capacity of the farmers leaves much to be desired. The research system has yet to develop location-specific optimal fertilizer rates and management practices. The extension system operates based on recommendations that show little variation across different environments. Therefore, inefficiencies and the associated output losses under modern technology use in Ethiopia are expected to be potentially high. Any maize production gain through efficiency improvement requires that the farmers' technical and allocative efficiencies in maize production be quantified and the underlying factors identified and studied.

5.3.1 Data and Empirical Procedures

The data used in this study come from a survey of 47 traditional maize producers and 51 hybrid maize producers in Meta district in eastern Ethiopia during the 2001/2002 cropping season. Meta district is a high potential maize production zone given its better rainfall amount and distribution, ranging between 900 and 1200 mm, and NEP is widely implemented to enhance food grains production especially maize. The surveyed farmers were randomly selected after an initial stratification of farm households in three PAs into participants and non-participants in the extension program. Due to shortage of supply, farmers had to be registered as participants in NEP to get hybrid maize seeds. Although some participant farmers produced both hybrid and traditional maize, the latter was limited to small garden plots mainly for green harvest in view of critical land shortages and the perceived high yield advantages of hybrid maize.

As described earlier, data were collected through frequent visits to the sample households' crop fields to carry out interviews and to take plot-level measurements and observations throughout the 2001/2002 agricultural year. Input data were collected on a fortnight basis by asking the farmer to recall his/her activities on that particular plot during the past two weeks. Data included the quantities of seed and fertilizer used, labor time disaggregated by source, gender, age, and field operation and other miscellaneous inputs. The prices of all purchased inputs were also collected during this time. Output data on all the quantities of cereals, pulses, and oil crops harvested from each plot were recorded. A separate survey was conducted to collect output price information from nearby markets during planting and harvesting times of the major crops. Moreover, area measurements were taken in square meters from each plot with assistance from the farmers themselves and these were later converted to hectares.

The production technology of the sample farmers is represented by a Cobb-Douglas production function. The specification is admittedly restrictive in terms of the maintained properties of the underlying production technology. However, as interest rests on efficiency measurement, and not on the analysis of the general structure of the production technology, the Cobb-Douglas production function provides an adequate representation of the production technology (Taylor et al., 1986; Kopp and Smith, 1980; Battese, 1992). Further, the self-dual nature of the Cobb-Douglas production function and its cost function provides a computational advantage in obtaining estimates of technical and allocative efficiency.

Although the efficiency decomposition technique requires that the functional form be self-dual, a series of preliminary likelihood ratio tests were conducted to see whether the choice of the Cobb-Douglas functional form would actually be inappropriate. The tests revealed that the Cobb-Douglas stochastic frontier model was, in fact, an adequate representation of the data for participant and non-participant farmers in Meta and Babile, given the specifications of the more flexible translog frontier model. It was only the preferred (aggregate) model for the two groups of farmers in Babile for which the translog production frontier model would be more appropriate. Nevertheless, very similar technical efficiency estimates were obtained from the aggregate Cobb-Douglas and translog models.

For the investigation of the technical, allocative and economic efficiencies of traditional and hybrid maize production, separate stochastic frontier production functions, of the following form, are estimated

$$\begin{aligned} \ln Y_k &= \beta_0 + \beta_1 \ln land + \beta_2 \ln labor + \beta_3 \ln fertilizer \\ &\quad + \beta_4 \ln materials + (v_k - u_k) \end{aligned} \tag{5.14}$$

where ln denotes the natural logarithm; Y denotes the total quantity of traditional or hybrid maize output in kg; *land* denotes the total land planted to traditional or hybrid maize in hectares; *labor* denotes the amount of family labor, exchange labor, and hired labor used in traditional or hybrid maize production in man-days[5]; *fertilizer* denotes the amount of chemical fertilizer used in traditional or hybrid maize production in kg; and *materials* denotes the

[5] A man-day is equivalent to 7 working hours in the study area.

implicit quantity index of seeds and chemicals used in traditional or hybrid maize production estimated as the value of all seeds and chemicals deflated by a weighted price index of the inputs, the weights being the share of each input in total cost. It has become a standard practice in efficiency analysis to include only the conventional inputs (i.e., land, labor, fertilizer, and other variable inputs) in the frontier production function. It is argued that the non-conventional inputs such as education, credit, and land quality influence output indirectly by raising the efficiency with which the conventional inputs especially land and labor are used. Therefore, the non-conventional inputs are used in the second stage analysis of factors influencing production efficiency.

The solution to the cost minimization problem in equation (5.15) is the basis for deriving the dual cost frontier, given the input prices (w_n), parameter estimates of the stochastic frontier production function ($\hat{\beta}$) in equation (5.14), and the input-orientated adjusted output level Y_k^{i*} in equation (5.7)

$$\underset{x}{\text{Min}}\, C = \sum_n w_n X_n \tag{5.15}$$

$$\text{Subject to } Y_k^{i*} = \hat{A}\prod_n X_n^{\hat{\beta}_n},$$

where $\hat{A} = \exp(\hat{\beta}_0)$.

Substitution of the cost minimizing input quantities into (5.15) yields the following dual cost function

$$C(Y_k^{i*}, w) = \mathrm{H} Y_k^{i*\mu} \prod_n w_n^{\alpha_n}, \tag{5.16}$$

where $\alpha_n = \mu\hat{\beta}_n$, $\mu = \left(\sum_n \hat{\beta}_n\right)^{-1}$, $\mathrm{H} = \frac{1}{\mu}\left(\hat{A}\prod_n \hat{\beta}_n^{\hat{\beta}_n}\right)^{-\mu}$. The input prices, w_n, are averages of observed prices per unit of the inputs used.

For the investigation of socio-economic and institutional factors influencing technical and allocative efficiency in traditional and hybrid maize production, a linear regression model is used. The variables that are hypothesized to influence efficiency in the Ethiopian context

(Assefa, 1995; Getachew, 1995) are: AGE (the age of the household head); RWEDUC (dummy for literacy of the household head in terms of reading and writing); PREDUC (dummy for attendance of primary education); CASHCR (amount of cash credit obtained); PLOTOWN (dummy for plot ownership that equals 1 if the plot is government-allocated and 0 if it has been sharecropped, rented in, or borrowed); EXTNSN (the number of visits to a farmer by an extension agent during the cropping season); PARTCPN (the number of years the farmer participated in extension programs); PLOTQ (plot quality dummy); LSTKUNT (livestock ownership in Livestock Units); OFINCM (amount of off-farm income obtained by the household); and KHATAR (area under khat , the main cash crop).

5.3.2 The Empirical Results

The maximum-likelihood (ML) estimates of the parameters of the stochastic frontier production function specified in equation (5.14) were obtained using the computer program LIMDEP 7.0 (Greene, 1995). These results are presented in Table 5.1. The standard ordinary least squares (OLS) estimates of the average production function are also presented for comparison.

For traditional maize, the signs of the slope coefficients of the stochastic production frontier are positive as expected. Land and labor inputs are highly significant while fertilizer and materials are not significant in traditional maize production in view of farmers' less reliance on purchased inputs. Based on restricted least squares regression, the hypothesis of CRTS was strongly rejected, indicating that traditional maize producers actually operated under DRTS. On the other hand, all the variables have turned out to be significant in determining hybrid maize output. The high elasticities of hybrid maize output with respect to land, labor, fertilizer and materials suggest that hybrid maize output is highly responsive to all these inputs. The hypothesis of CRTS was strongly rejected, indicating that hybrid maize producers operated under IRTS. This may be due to the fact that relatively small plots of land are planted to hybrid maize because of land shortages and seed supply constraints in the area as is the case with other parts of the country.

The estimate of the variance parameter, λ, is significant in both traditional and hybrid maize production implying that the inefficiency effects, as opposed to the random factors, are significant in determining the level and variability of traditional and hybrid maize output of farmers in the study area. This is also shown in Table 5.1 by the higher variance of the inefficiency term (0.293 for traditional maize and 0.101 for hybrid maize) than that of the random error term (0.074 for traditional maize and 0.048 for hybrid maize). Therefore, variation in maize output level across farmers is mainly due to factors within the control of farmers and not due to random factors beyond their control like weather and disease. Alternatively, the traditional production function with no technical inefficiency effects is not an adequate representation of the data.

Table 5.1: OLS and ML estimates of the alternative maize production functions

	Traditional Maize (N=47)			Hybrid Maize (N=51)		
Variable	Mean (S.D.)	OLS estimates	ML estimates	Mean (S.D.)	OLS estimates	ML estimates
Intercept	-	5.389*** (0.724)	5.507*** (0.704)	-	5.133*** (0.505)	5.264 *** (0.650)
ln (Land)	0.26 (0.13)	0.352* (0.213)	0.297** (0.121)	0.32 (0.16)	0.343*** (0.105)	0.357 *** (0.101)
ln (Labor)	25.32 (14.21)	0.388*** (0.152)	0.437*** (0.119)	48.94 (44.55)	0.360*** (0.053)	0.345*** (0.061)
ln (Fertilizer)	15.32 (11.30)	0.042 (0.054)	0.027 (0.054)	30.46 (16.77)	0.283*** (0.092)	0.242** (0.119)
ln (Materials)	11.13 (6.32)	0.019 (0.114)	0.064 (0.132)	4.96 (4.46)	0.188* (0.105)	0.165* (0.098)
Function coefficient	-	0.801	0.825		1.174	1.109
F or X^2-statistic (CRTS)	-	41.43*** (F)	42.89*** (X^2)		109*** (F)	95.2*** (X^2)
R^2		0.86			0.87	
λ			1.989* (1.142)			1.461* (0.893)
σ^2_v			0.074			0.048
σ^2_u			0.293			0.101
Log-likelihood			-25.52			-8.87

Notes: *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.1 level.
S.D. = standard deviation. Figures in parentheses represent asymptotic standard errors.

Source: Own computation.

The dual frontier cost function for hybrid maize, derived analytically from the stochastic production frontier shown in Table 5.1, is given as

$$\ln C_h = -3.728 + 0.322 \ln w_A + 0.311 \ln w_L + 0.218 \ln w_F + 0.149 \ln w_M + 0.902 \ln Y_k^{i*}. \tag{5.17}$$

The corresponding dual cost frontier for traditional maize production is similarly derived and is given as

$$\begin{aligned} \ln C_t = & -5.653 + 0.360 \ln w_A + 0.530 \ln w_L + 0.033 \ln w_F \\ & + 0.077 \ln w_M + 1.211 \ln Y_k^{i*} . \end{aligned} \tag{5.18}$$

where C_h and C_t are, respectively, per-farm costs of producing hybrid and traditional maize, respectively; Y_k^{i*} is total maize output in kg of the k^{th} farm adjusted for any statistical noise and scale effects as specified in equation (5.7); w_A is the seasonal rent of a hectare of land estimated at 1000 Birr; w_L is the wage rate estimated at 7 Birr/day; w_F is the price of fertilizer estimated at 2.75 Birr/kg; and w_M is the price index of materials (i.e., seeds and chemicals) estimated at 6 Birr/kg for hybrid maize and 1.5 Birr/kg for traditional maize production. Inadequate farm level price data coupled with little or no input price variation across farms in Ethiopia precludes any econometric estimation of a cost or profit frontier function. Therefore, the use of self-dual production frontier functions allows the cost frontier to be derived and used to estimate economic efficiency in situations where producers face the same input prices.

5.3.2.1 Maize Production Efficiency Estimates

The frequency distributions and summary statistics of both the scale-adjusted and conventional efficiency measures for traditional and hybrid maize production are presented in Table 5.2. For traditional maize, the estimated scale-adjusted mean TE, AE, and EE indices are 68 percent, 83 percent, and 56 percent, respectively, and the corresponding results for hybrid maize production are 78 percent, 77 percent, and 61 percent, respectively. The results indicate that hybrid maize production is more technically and economically efficient than traditional maize production. The higher average technical efficiency of hybrid maize production compared with traditional maize production is consistent with the higher average yields of hybrid maize (5100 kg/ha) than local maize (2030 kg/ha) as shown in Table 5.4.

The conventional mean TE, AE, and EE indices for traditional maize production are 62 percent, 83 percent, and 51 percent, respectively, confirming that the conventional technical and economic efficiency measures are consistently and proportionally lower than the scale-adjusted measures under the DRTS technology in traditional maize production. The corresponding conventional measures for hybrid maize production are 80 percent, 77 percent, and 62 percent, confirming that the conventional approach consistently overestimates the technical and economic efficiency measures under IRTS technology.

The conventional TE and EE measures are consistently lower than the scale-adjusted measures under the DRTS technology (e.g., traditional maize production) and higher under the IRTS technology (e.g., hybrid maize production). Using the paired-difference *t*-test of the conventional and scale-adjusted mean efficiency measures, the conventional mean TE and EE measures were significantly lower than the corresponding scale-adjusted efficiency measures in traditional maize and higher in hybrid maize production (Table 5.2). The scale-adjusted and conventional AE measures were found to be identical, confirming that the scale-adjusted TE and EE measures are actually a neutrally scaled version of the corresponding conventional measures. Depending on the returns to scale, a neutrally scaled-up or scaled-down conventional TE and EE estimates ensure identical conventional and scale-adjusted AE measures. Taylor et al. (1986), following the conventional technique, obtained considerably lower average TE (17 percent) and EE (13 percent) when the AE measure, that is not sensitive to scale effects, was 74 percent for traditional farming in Brazil. This certainly confirms that the TE and EE measures they obtained from the conventional approach actually underestimated the true measures and the conclusions drawn could be very misleading.

Figure 5.2 depicts the distribution of the scale-adjusted and conventional technical efficiency measures whereas Figure 5.3 presents the corresponding economic efficiency distributions. Figure 5.2 shows that, for traditional maize production, the conventional approach classifies a greater proportion of farmers in the technical efficiency ranges less than 50 percent and a smaller proportion in the ranges greater than 50 percent than does the scale-adjusted approach. Further, while some farmers achieved scale-adjusted technical efficiency greater than 90 percent, no farmer is classified in this range based on the conventional approach. This confirms that the conventional approach consistently underestimates the true individual technical efficiency measures such that the conventional technical efficiency distribution is also a neutral downward shift of the true distribution under decreasing returns to scale.

Figure 5.2 also shows that, for hybrid maize production, the conventional approach classifies a greater proportion of farmers in the technical efficiency ranges between 80 and 100 percent and a smaller proportion in the ranges between 60 percent and 80 percent than does the scale-adjusted approach. This confirms that the conventional approach consistently overestimates the true individual technical efficiency measures such that the conventional technical efficiency distribution is also a neutral upward shift of the true distribution under increasing returns to scale. Figure 5.3, on the other hand, shows that, for traditional maize production, the conventional approach classifies a greater proportion of farmers in the economic efficiency ranges less than 50 percent and a smaller proportion in the ranges greater than 50 percent than does the scale-adjusted approach. This again confirms that the conventional approach consistently underestimates the true individual economic efficiency measures such that the conventional economic efficiency distribution is also a neutral downward shift of the true distribution under decreasing returns to scale.

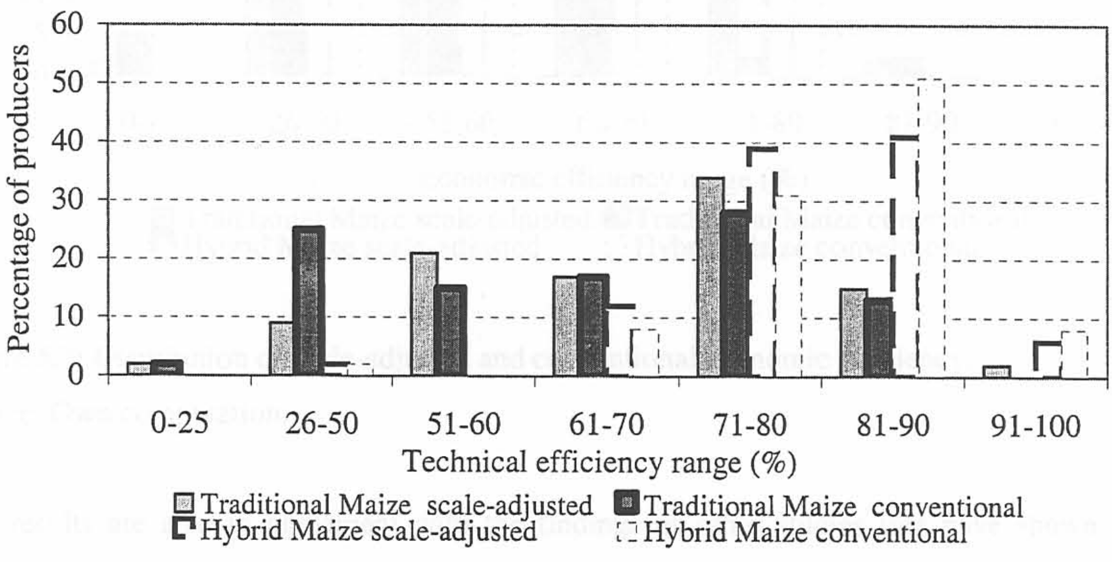

Figure 5.2: Distribution of scale-adjusted and conventional technical efficiency.
Source: Own computation.

Figure 5.3 also shows that, for hybrid maize production, the conventional approach classifies a greater proportion of farmers in the economic efficiency ranges between 60 and 80 percent and a smaller proportion in the ranges between 25 and 60 percent than does the scale-adjusted approach. This confirms that the conventional approach consistently overestimates the true individual economic efficiency measures so that the conventional economic efficiency distribution is also a neutral upward shift of the true distribution under increasing returns to scale. Based on the scale-adjusted measures, a 56 percent EE indicates that traditional maize producers can increase maize production by an average 44 percent by operating at full technical and allocative efficiency levels. The results suggest that a considerable part of economic inefficiency under traditional technology is due to technical inefficiency. This is consistent with the Schultzian argument that traditional farmers are allocatively efficient in view of their accumulated experience in allocating own resources and their less use of purchased inputs.

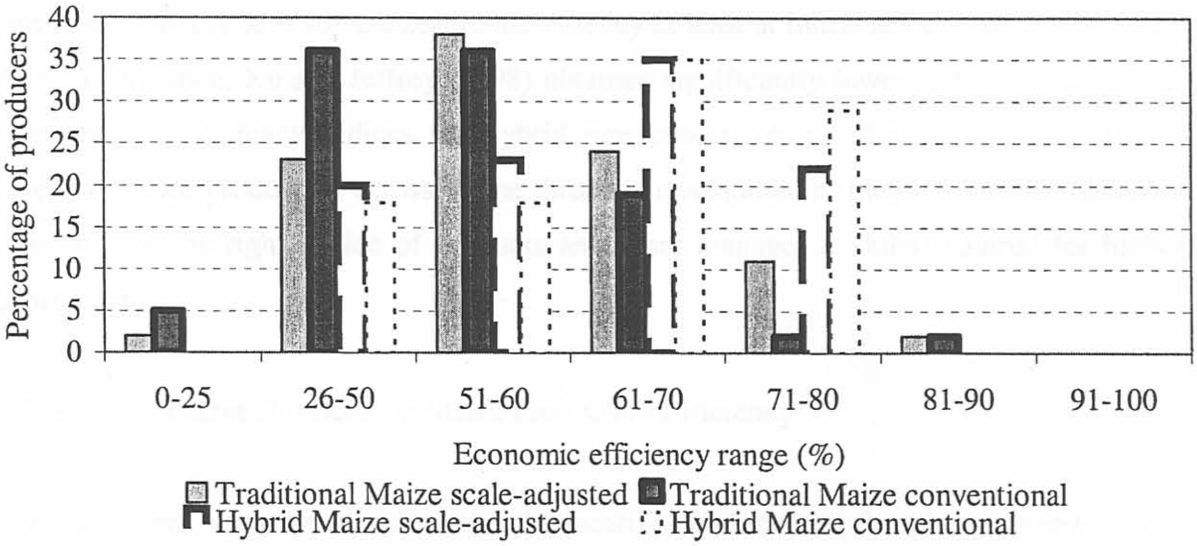

Figure 5.3: Distribution of scale-adjusted and conventional economic efficiency.
Source: Own computation.

The results are also in agreement with the findings of other studies that have shown the existence of substantial technical inefficiencies in developing agricultural economies and the consequent implications for agricultural growth possibilities with existing resources and technology. For example, high technical inefficiency has been found to exist among cereal producers in Ethiopia (Getu et al., 1998; Getachew, 1995; Corppenstedt and Abbi, 1996), suggesting that technical efficiency improvement is one of the possible avenues for increasing cereals production with available resources and (traditional) technology. For hybrid maize production, a 61 percent EE indicates that farmers can increase hybrid maize output by an average 39 percent by operating at full technical and allocative efficiency levels. Technical and allocative inefficiencies in hybrid maize production make equivalent contribution to the observed high economic inefficiency.

The results suggest that the potential of hybrid maize technology is underutilized and its use causes substantial allocative errors on the part of the producers. Efficient use of new technologies is possible only if farmers have adequate technical and financial support through the extension and credit systems, and adequate and timely provision of inputs and information. For instance, Seyoum et al. (1998) obtained an average TE score of 94 percent for maize producers within the SG project in eastern Ethiopia. The purpose of the SG project was mainly to demonstrate packages of technologies on farmers' own plots with substantial technical support and credit services and hence production was technically superior. Unlike project-level use of new technology, wider dissemination of the program to the farming community is likely to involve sizeable inefficiency at least at initial stages (Ali and Byerlee, 1991). For instance, Xu and 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 as they needed time to reach full operation, the right choice of products and other managerial skills required for higher performance.

5.3.2.2 Factors Influencing Maize Production Efficiency

Maize producers' variation in technical and allocative efficiency levels are hypothesized to be due to several farm and farmer attributes, mainly reflecting the managerial ability of farmers and their access to information. An OLS estimation procedure was employed to identify the important socio-economic and institutional factors influencing technical and allocative efficiency. The parameter estimates of the OLS regression are presented in Table 5.3. As can be judged based on the R^2 values of the four regressions and the corresponding F-statistics, the model fits the data reasonably well. Technical efficiency in traditional maize production is positively and significantly influenced by age, education, and plot quality. This suggests that farmers acquire better management skills for traditional maize production through experience and education. Moreover, plot quality differences cause technical efficiency variation among traditional maize farmers due to the fact that some farmers in the wet highland zone allocated degraded land to maize while most farmers planted the most fertile plots in their homestead to maize. The rest of the variables, including extension, credit, off-farm income, livestock unit, and the area under khat have the expected positive signs but are insignificant.

Table 5.2: Scale-adjusted and conventional maize production efficiencies

Level (percent)	TE Number of farmers (percent farmers)				AE Number of farmers (percent farmers)				EE Number of farmers (percent farmers)			
	Traditional Maize		Hybrid Maize		Traditional Maize		Hybrid Maize		Traditional Maize		Hybrid Maize	
	scale-adjusted	conventional	Scale-adjusted	conventional	scale-adjusted	conventional	scale-adjusted	conventional	scale-adjusted	conventional	scale-adjusted	conventional
<25	1(2)	1(2)	-	-	-	-	-	-	1(2)	2 (5)	-	-
26-50	4(9)	12(25)	1(2)	1(2)	1(2)	1(2)	-	-	11(23)	17(36)	10(20)	9(18)
51-60	10(21)	7(15)	-	-	-	-	2(4)	2(4)	18(38)	17(36)	12(23)	9(18)
61-70	8(17)	8(17)	6(12)	4(8)	3(7)	3(7)	11(22)	11(22)	11(24)	9(19)	18(35)	18(35)
71-80	16(34)	13(28)	20(39)	16(31)	9(19)	9(19)	16(31)	16(31)	5(11)	1(2)	11(22)	15(29)
81-90	7(15)	6 (13)	21(41)	26(51)	24(51)	24(51)	17(33)	17(33)	1(2)	1(2)	-	-
91-100	1(2)	-	3 (6)	4(8)	10(21)	10(21)	5(10)	5(10)	-	-	-	-
Mean	68	62	78	80	83	83	77	77	56	51	61	62
Minimum	20	14	41	44	49	49	57	57	18	12	30	33
Maximum	91	88	93	93	96	96	91	91	86	84	76	86
t-ratio (paired-difference)		-24***		20.51***		0.00		0.00		-21***		19.85***

Note: *** = Paired-difference of means significant at 0.01 level. The *t*-ratios are based on the paired-difference *t*-test.

Source: Own computation.

Technical efficiency in hybrid maize production is positively and significantly influenced by basic education, credit, and plot quality, suggesting that better utilization of new maize technology is facilitated by education through its effect on acquiring and using information, by credit through its effect on farmers' ability to settle the required down payments for input credit, and by plot quality through its effect on supplementing the high fertilizer requirements of hybrid maize against the background of low fertilizer application rates coupled with highly degraded land in the wet highland zone.

Age has turned out to negatively and significantly influence technical efficiency, suggesting that farmers who have accumulated experience in traditional farming are less likely to easily change their traditional practices to more modern ones as required by new varieties. Seyoum et al. (1998) also obtained a negative and significant influence of age on the technical efficiency of maize producers within the SG project in eastern Ethiopia. The extension variable, though positive, is not significant. Seyoum et al. (1998) also obtained a positive but insignificant influence of extension advice on the technical efficiency of maize producers within the SG project.

Table 5.3: Factors influencing efficiency of maize production in Meta

Variable	Traditional Maize		Hybrid Maize	
	TE	AE	TE	AE
Constant	-0.093 (-0.231)	2.056*** (14.235)	3.267*** (9.365)	2.367*** (9.310)
AGE	0.135* (2.023)	0.082 (1.229)	-0.206* (-1.931)	-0.035 (-0.232)
EXTNSN	0.142 (1.231)	0.102 (1.0325)	0.054 (1.326)	0.134 (1.035)
RWEDUC	0.265*** (3.299)	0.125 (1.230)	0.369*** (4.236)	0.102 (1.369)
PREDUC	0.095 (1.332)	0.256** (1.985)	0.021 (1.234)	0.323*** (2.367)
PLOTOWN	0.021 (1.200)	0.130 (1.357)	0.022 (1.233)	0.223* (1.811)
CASHCR	0.027 (0.106)	0.402** (1.95)	0.195** (2.325)	0.186* (1.752)
PARTCPN	0.023 (1.114)	0.024 (1.355)	0.133 (1.200)	0.206 (1.378)
LSTKUNT	0.103 (1.06)	0.127 (1.201)	-0.015 (-1.026)	0.098 (1.058)
OFINCM	0.012 (1.025)	0.188 (1.102)	0.140 (1.023)	0.208 (1.455)
PLOTQ	0.432*** (4.235)	0.023 (1.388)	0.233*** (2.369)	0.023 (1.027)
KHATAR	0.106 (1.265)	0.108 (1.354)	-0.025 (-1.235)	0.087 (1.0248)
R^2	0.65	0.47	0.55	0.53
F	12.548***	12.42***	4.236***	2.065***

Notes: *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level.
Figures in parentheses are t-ratios.

Source: Own computation.

Allocative efficiency in traditional as well as hybrid maize production is positively and significantly influenced by primary education and credit. The significant influence of primary as opposed to basic education on allocative efficiency suggests that allocative efficiency requires greater skills and knowledge that does technical efficiency. Farmers with better education and access to credit have more information and capacity for optimal allocation of traditional and new inputs. This is also consistent with the findings of Assefa and Heidhues (1996) for cereals producers in the central highlands of Ethiopia and Sharma et al. (1999) for swine producers in Hawaii. Allocative efficiency in hybrid maize production is also positively and significantly influenced by plot ownership, suggesting that owner cultivators are more allocatively efficient than non-owner cultivators. This may be due to sub-optimal applications of fertilizer and seeds on sharecropped, rented in and borrowed lands. These plots received, on average, 66 kg fertilizer and 11 kg seeds per hectare, whereas owned plots received, on average, 114 kg fertilizer and 19 kg seed per hectare when the recommended rates are 200 kg fertilizer and 25 kg seed per hectare. Hayami and Otsuka (1993) argued that informal contractual tenure arrangements such as sharecropping and other forms of indigenous land tenure rights result in an inefficient allocation of resources as well as reduced incentives to improve agricultural lands.

5.3.3 Conclusions

Using an extended efficiency decomposition technique to maize production in eastern Ethiopia, we obtained mean technical, allocative, and economic efficiency indices, respectively, of 68 percent, 83 percent, and 56 percent for traditional maize and 78 percent, 77 percent, and 61 percent for hybrid maize production. The results confirmed that the conventional efficiency decomposition approach actually overestimates efficiency measures under increasing returns to scale and underestimates under decreasing returns to scale. Because of proportional upward or downward biases of the conventional technical and economic efficiency estimates relative to the scale-adjusted estimates, both the conventional and scale-adjusted allocative efficiency measures have turned out to be identical. Economic inefficiency in traditional maize production is dominated by technical inefficiency, suggesting that improvement of technical efficiency needs a priority attention as it provides a significant source of growth in maize output. Economic inefficiency in hybrid maize production, on the other hand, is equally dominated by technical and allocative inefficiency, suggesting that both technical and allocative inefficiencies are equally relevant targets that need to be overcome to enhance the production of hybrid maize. An examination of the relationship between efficiency and various socio-economic and institutional variables revealed that education, access to credit, and greater security of tenure are the key determinants of the efficiency of maize producers.

5.4 Empirical Analysis of Overall Farm Level Production Efficiency of Smallholders

Low agricultural productivity and adverse climatic conditions have been largely responsible for the growing gap between food demand and supply in Ethiopia. One of the major policy shifts since the change of government in 1992 has been the substantial emphasis placed on improving the productivity of peasant agriculture through increased use of a package of improved agricultural technologies. The Ethiopian government introduced NEP based on the experiences of SG project, which embarked upon the popularization of large-scale (usually half-hectare) on-farm demonstration plots for already available improved agricultural production technologies. NEP was designed with the aim of improving the productivity of smallholder farmers through better access to and use of improved production technologies such as fertilizer, improved seeds, pesticides and better cultural practices mainly for cereal crops such as maize, wheat, and tef.

Despite considerable yield increments obtained from the demonstration plots of the SG project in the high potential agricultural areas, cereal yields have rather stagnated following large-scale applications of improved production technologies in recent years. This has become a source of growing concern regarding the effectiveness of NEP on the efficiency with which smallholders use their limited resources through the use of improved technologies. The success of NEP depends critically on how well the three functions of extension, credit and input delivery meet the particular needs of smallholders, a situation very different from that of SG project which was limited to specific high potential zones with relatively better functioning credit and input delivery services (Befekadu and Berhanu, 1999; Mulat, 1999).

There is, however, lack of adequate empirical evidence of whether NEP has actually enhanced production efficiency in different agro-climatic zones, given a package of improved technologies. One of the objectives of this study was, therefore, to assess the impact of NEP on the technical and allocative efficiency of farmers and to identify the underlying factors influencing farmer efficiency in eastern Ethiopia.

5.4.1 Data and Empirical Procedures

The data for this study come from two samples of farmers, one sample composed of farm households participating in the extension program and another composed of non-participant farm households, in two selected districts, Meta and Babile, each representing distinct agro-climatic zones in eastern Ethiopia. Meta district was selected to represent a typical wet highland zone where there is very high population pressure on land (see Table 5.4) and receives relatively better rainfall amount and distribution ranging between 900 and 1200 mm per annum. Meta is a high potential cereal production zone where NEP is widely implemented to enhance the production of food grains. The most widely grown cereals in Meta are maize, barley and wheat. On the other hand, Babile district was selected to represent a dry land zone receiving an annual rainfall between 500 and 700 mm and has got an average altitude of 1650 masl. Babile is an important target of NEP and NGO's activities in view of widespread food insecurity. Dry land technologies generated by Alemaya University and other research centers are mainly tested and promoted in Babile. Technologies include short-cycle, drought-tolerant, and better yielding varieties of maize and sorghum along with the appropriate fertilizer recommendations and agronomic practices. Sorghum, maize and groundnuts are widely grown in Babile.

The surveyed farmers were randomly selected after an initial stratification of farm households in three PAs into participants and non-participants in the extension program. The participant and non-participant sample farm households surveyed in Meta were, respectively, 53 and 47, whereas 50 farm households from each group were surveyed in Babile. Data were collected through frequent visits to the sample farm households' crop fields to carry out interviews and to take plot-level measurements and observations throughout the 2001/2002 agricultural year. Input data were collected on a fortnight basis by asking the farmer to recall his/her activities during the past two weeks. Data included the quantities of seed and fertilizer used, labor time disaggregated by source, gender, age, and field operation and other miscellaneous inputs. The prices of all purchased inputs were also collected during this time. Output data on all the quantities of cereals, pulses, and oil crops harvested were collected. A separate survey was conducted to collect output price information from Muti, Chelenko and Babile markets during planting and harvesting times of the major crops.

A summary of the values of the variables used in the crop level and farm level efficiency analyses is presented in Table 5.4. Participants in NEP in both districts obtained higher average crop output value per hectare of cultivated land in view of higher average yields of the major crops, including maize, sorghum, groundnuts, wheat and barley.

Table 5.4: Summary statistics of the variables used in the efficiency analyses

	Meta		Babile	
	Participants	Non-participants	Participants	Non-participants
Variable	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Value of crop output (Birr/ha)	3350 (1306)	1490 (769)	3660 (1508)	1471 (714)
Hybrid maize yield (kg/ha)	5100 (2460)	---	---	---
Local maize yield (kg/ha)	2040 (670)	2030 (1300)	1070 (740)	930 (550)
Sorghum yield (kg/ha)	---	1460 (1000)	1100 (510)	980 (470)
Groundnuts yield (kg/ha)	---	---	740 (390)	670 (300)
Wheat yield (kg/ha)	2000 (920)	1700 (1070)	---	---
Barley yield (kg/ha)	1380 (970)	1420 (2150)	---	---
Cultivated land (ha)	0.73 (0.60)	0.65 (0.16)	1.70 (0.66)	1.45 (0.60)
Labor (Man-days/ha)	65 (32)	68 (16)	57 (29)	53 (80)
Fertilizer (kilogram/ha)	69 (36)	22 (24)	42 (12)	17 (10)
Age	39 (12)	41 (12)	37 (10)	38 (10)
Education (literacy) dummy	0.77 (0.35)	0.66 (0.31)	0.66 (0.42)	0.40 (0.26)
Off-farm income (Birr)	209 (62)	91 (143)	327 (91)	287 (28)
Extension visit	6 (3)	0.8 (1)	8 (7)	4 (3)
Man equivalent	1.58 (0.8)	1.39 (0.53)	1.57 (0.57)	1.45 (0.57)
Cash credit (Birr)	71 (96)	32 (78)	337 (421)	50 (21)
Livestock Unit	2.47 (1.69)	2.04 (1.24)	5.67 (0.59)	3.90 (0.45)
Maize-potato share (percent)	54 (12)	63 (33)	---	---
Cereal-Pulse share (percent)	8 (2)	11 (5)	45 (10)	39 (13)

Note: S.D. = Standard deviation.

Source: Own computation.

The differences between the two groups of farmers in terms of yields of major crops is substantial in the case of maize. While they obtained comparable local maize yields, the participants obtained higher hybrid maize yields in view of the maize technology package promoted by NEP. Moreover, the participants have higher cultivated land, livestock units, off-farm income, cash credit, household labor, and extension visits than the non-participants. Both groups of farmers in Meta have comparably high average percentage of cultivated area allocated to the maize-potato cropping system, which provides greater opportunities for efficient use of land in the face of increasing land shortages in the wet highland zone. Both participants and non-participants in Meta and Babile applied far less amount of fertilizer per hectare of cultivated land than recommended. This is due to shortage of supply of improved seeds, shortage of cash credit to buy fertilizer or to settle the required down payments for fertilizer credit, and production and price risks. For example, highly depressed maize prices following increased maize production have greatly undermined the profitability of improved technologies especially fertilizer and the consumption of fertilizer has shown a declining trend over the last 3 years.

In view of the increasing pressure on land in the wet highland zone, both participant and non-participant farmers in Meta have less average cultivated land and livestock than farmers in the dry land zone, Babile. Both groups of farmers in Babile have comparably high average percentage of cultivated area allocated to the cereal-pulse cropping system, which offers opportunities for crop diversification to cope with the risk of crop failure due to drought as well as for improving yield through soil fertility improvement and better control of pests and diseases (Bezabih, 2000).

The objective of the farm level production efficiency analysis is to assess the impact of NEP on the technical, allocative, and economic efficiency of smallholder farmers. However, because it is impossible to observe a farmer with and without program participation simultaneously, and lacking a panel data set that allows observation of households before and after program participation, impact analysis in this study is based on comparing production efficiency estimates differentiated by participation in NEP. It could be argued that if certain socio-economic factors such as education, access to land, and family size affect a household's participation in NEP or acceptance into NEP, selection bias results and attribution becomes difficult. This type of selection bias may lead to either overestimation or underestimation of impact depending on the farmers' initial socio-economic conditions. However, farmers in the study areas choose to participate in NEP and there is no specific target group of farmers served by the program. Although there seem to be clear differences between the two groups in some of the socio-economic characteristics as shown in Table 5.3, these differences are not significant. Moreover, differences in education, credit access, livestock ownership, and income could actually be brought about by NEP itself and hence do not imply selection bias and differing initial conditions of the two groups of farmers. Therefore, production efficiency analysis differentiated by participation in NEP is a reasonable approach to measuring the impact of the program on the efficiency of farmers.

Like the crop level analysis, the production technology of the sample farmers for the farm level efficiency analysis is represented by a Cobb-Douglas production function. For the investigation of the technical, allocative, and economic efficiencies of participant and non-participant farmers, separate stochastic frontier production functions, of the following form, are estimated for each group of farmers

$$\begin{aligned}\ln Y_i = \beta_0 + \beta_1 \ln \mathit{land} + \beta_2 \ln \mathit{labor} \\ + \beta_3 \ln \mathit{fertilizer} + \beta_4 \ln \mathit{materials} + (v_i - u_i),\end{aligned} \tag{5.19}$$

where ln denotes the natural logarithm; Y_i denotes the gross value of crop output of the i^{th} farmer; *land* denotes the total cultivated land in hectares; *labor* denotes the total amount of labor used in crop production in man-days; and *materials* denotes the implicit quantity index of seeds and chemicals used in crop production.

The solution to the farm level cost minimization problem like in equation (5.15) is the basis for deriving the dual farm level cost frontier, given the input prices (w_n), parameter estimates of the stochastic frontier production function ($\hat{\beta}$), and the input-orientated adjusted output level, Y_i^*. The investigation of factors influencing the technical and allocative efficiencies of participant and non-participant farmers is carried out by estimating the same regression model used for the crop level analysis. Most of the variables that are hypothesized to influence crop level technical and allocative efficiency also affect farm level technical and allocative efficiency. The variables that are hypothesized to influence farm level production efficiency in the Ethiopian context (Assefa, 1995; Getachew, 1995) are: AGE (the age of the household head); RWEDUC (dummy for literacy of the household head in terms of reading and writing); PREDUC (dummy for attendance of primary education); CASHCR (amount of cash credit obtained); FARMSZ (the size of cultivated land in hectares); EXTNSN (the number of visits to a farmer by an extension agent during the cropping season); PARTCPN (the number of years the farmer participated in previous extension programs); HHLABR (household labor availability in man equivalents); LSTKUNT (livestock ownership in Livestock Units); OFINCM (amount of off-farm income obtained by the household); CERPULS (percentage of cultivated area allocated to the cereal-pulse cropping system) for Babile; MZPOT (percentage of cultivated area allocated to the maize-potato cropping system) for Meta; and MKTDIST (distance to the district market in walking minutes).

5.4.2 The Empirical Results

The maximum-likelihood (ML) estimates of the parameters of the stochastic frontier production function are presented in Table 5.5. The ordinary least squares (OLS) estimates of the average production functions are also presented for comparison. The OLS estimates are only slightly different from the ML estimates in the case of the participant farmers in the wet highland zone of Meta while the differences between the two estimates become substantial in the case of non-participant farmers in Meta and the aggregate sample in Babile. This is a preliminary indication of the relatively lower level of technical efficiency among the non-participants in Meta and the aggregate sample farmers in Babile, because a higher similarity in the two estimates is actually associated with higher technical efficiency. The use of the SFPF is justified by the presence of the one-sided inefficiency term in the production function that is not accounted for in the traditional average production functions. From this it follows that as long as output variations among farmers due to inefficiency are believed to be negligible, there is little or no reason to expect the OLS estimates of the average production function and the ML estimates of the SFPF to be different.

A common stochastic frontier model for all farmers in each of the districts, irrespective of whether they participated in NEP, was estimated to see if the two samples of farmers actually used different technologies. Using the generalized likelihood ratio (LR) test (Coelli and Battese, 1996), the aggregate model for Babile could not be rejected while the corresponding model for Meta was strongly rejected[6]. This indicates that while the participant and non-participant farmers actually used different production technologies in the wet highland zone, those in the dry land zone used homogenous technologies. This confirms the serious shortage of improved technologies for Babile, as is the case with other moisture-stressed agro-climatic zones (Bezabih, 2000). Therefore, the aggregate model for Babile was chosen as the preferred model to predict the efficiency indices for both groups of farmers.

Table 5.5: OLS and ML estimates of the alternative crop production functions

Variable	Meta				Babile	
	Participants		Non-Participants		Aggregate	
	OLS estimates	ML estimates	OLS estimates	ML estimates	OLS estimates	ML estimates
Intercept	6.174***	6.632***	5.624***	6.013***	6.069***	6.615***
	(19.414)	(19.785)	(10.968)	(12.146)	(19.053)	(24.374)
ln (Land)	0.262***	0.330***	0.884***	0.747**	0.415***	0.433***
	(3.372)	(3.774)	(2.500)	(2.095)	(3.477)	(3.631)
ln (Labor)	0.179***	0.171**	0.309**	0.256*	0.145***	0.183***
	(2.669)	(2.011)	(2.183)	(1.787)	(2.990)	(3.812)
ln (Fertilizer)	0.140**	0.118**	0.069	0.063	0.141***	0.098**
	(2.152)	(2.105)	(1.168)	(0.971)	(3.991)	(1.936)
ln (Materials)	0.111***	0.092**	0.044	0.075	0.089	0.058
	(3.028)	(2.454)	(0.738)	(1.208)	(1.031)	(0.796)
R^2	0.82		0.60		0.70	
Function Coefficient		0.703		1.141		0.772
λ		4.146*		2.332*		2.729***
		(1.715)		(1.624)		(2.513)
σ_u^2		0.978		0.195		0.283
σ_v^2		0.006		0.036		0.038
Log-likelihood		12.64		-12.919		-39.57

Notes: *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.1 level.
Figures in parentheses represent asymptotic t-ratios.

Source: Own computation.

As expected, the output elasticities of all variables are positive in all SFPF specifications. Land has the highest output elasticity in the study areas especially in Meta among the non-participant farmers who are cultivating extremely small plots of land (Table 5.4) with the result that they seem to operate in an irrational production zone. For participants in Meta, all input variables are positive and highly significant in determining crop production. For non-

[6] The LR test-statistic for the null hypothesis of aggregate function is equal to 8 for Babile and 12 for Meta compared to 9.5, the 95 percent χ^2 critical value with 4 degrees of freedom.

participants in Meta, who have no access to input credit and can neither afford to buy adequate amounts fertilizer and chemicals, these variables are not statistically significant.

The estimate of the variance parameter, λ, is significant in the SFPF of both participant and non-participant farmers in both districts implying that the inefficiency effects are significant in determining the level and variability of crop production in the study areas. Therefore, variation in food crop output level across farmers is mainly due to factors under their control and not to the random factors beyond their control like weather and disease.

The dual frontier cost function for participant farmers in Meta, derived analytically from the stochastic production frontier shown in Table 5.5, is derived as

$$\ln C_i = -7.107 + 0.464 \ln w_A + 0.240 \ln w_L + 0.166 \ln w_F + 0.129 \ln w_M + 1.406 \ln Y_i^* . \tag{5.20}$$

The dual cost frontier for non-participants in Meta is given as

$$\ln C_i = -4.132 + 0.655 \ln w_A + 0.225 \ln w_L + 0.055 \ln w_F + 0.065 \ln w_M + 0.876 \ln Y_i^* . \tag{5.21}$$

The dual cost frontier for all sample farmers in Babile is given as

$$\ln C_i = -7.445 + 0.561 \ln w_A + 0.236 \ln w_L + 0.127 \ln w_F + 0.075 \ln w_M + 1.295 \ln Y_i^* . \tag{5.22}$$

where C_i is the minimum cost of production of the i^{th} farmer; Y_i^* is the index of output adjusted for any statistical noise and scale effects; w_A is the seasonal rent of a hectare of land estimated at 1000 Birr/ha for Meta and 600 Birr/ha for Babile; w_L is the wage rate estimated at 7 Birr/day; w_F is the price of fertilizer estimated at 2.75 Birr/kg; and w_M is the price index of seeds and chemicals estimated at 1.5 Birr/kg.

5.4.2.1 Farm Level Efficiency Estimates

Using the cost frontiers and average input prices, the scale-adjusted[7] technical, allocative, and economic efficiency indices are computed for each producer. The frequency distributions and summary statistics of these indices for participant and non-participant farmers in NEP are presented in Tables 5.6 and 5.7.

Table 5.6: Crop production efficiency distributions in Meta

Level (percent)	TE Number of farmers (percent farmers)		AE Number of farmers (percent farmers)		EE Number of farmers (percent farmers)	
	Participants	Non-participants	Participants	Non-participants	Participants	Non-participants
<50	-	5(11)	-	4(9)	9(17)	13(28)
51-60	6(11)	5(11)	3(6)	2(4)	13(24)	8(17)
61-70	5(10)	7(15)	8(15)	1(2)	21(40)	11(23)
71-80	11(21)	12(25)	22(41)	4(9)	10(19)	10(21)
81-90	25(47)	16(34)	15(28)	12(25)	-	5(11)
91-100	6(11)	2(4)	5(9)	24(51)	-	-
Mean	79 [a]	72 [a]	80 [b]	85 [b]	65	63
Minimum	50	37	52	26	36	24
Maximum	97	93	95	99	80	85

[a, b] Means significantly different at 0.05 level.

Source: Own computation.

For participant farmers in Meta, the estimated mean technical, allocative, and economic efficiency indices are 79 percent, 80 percent, and 65 percent, respectively, whereas the corresponding results for non-participants are 72 percent, 85 percent, and 63 percent. The results indicate that both participant and non-participant farmers exhibit comparably high economic inefficiencies due to their low technical and allocative efficiencies in food crop production. Relative to their respective technologies, the participants have, on average, higher technical but lower allocative efficiencies than the non-participant farmers, with the result that both groups have similar economic inefficiencies. The participants and non-participants can gain, respectively, an average crop output growth of 35 percent and 37 percent through

[7] As the extended efficiency decomposition technique is already demonstrated in the preceding section, the farm level efficiency estimates reported are the scale-adjusted measures.

improvements in both technical and allocative efficiency with their respective technologies. Moreover, the hypotheses of equal technical and allocative efficiencies between the two groups of farmers were rejected, implying that although NEP improved technical efficiency it rather caused considerable allocative inefficiencies among participant farmers in Meta.

Therefore, due to the counteracting impacts of NEP, the hypothesis of equal economic efficiencies could not be rejected, implying that both actually encountered similar levels of economic efficiencies. The results thus suggest that although NEP improved the technical efficiency of participant farmers in Meta, given their improved technology, it rather induced greater allocative inefficiencies and hence didn't impact on overall productive efficiencies.

For participant farmers in Babile, the results in Table 5.7 show that the mean technical, allocative, and economic efficiency indices are 68 percent, 81 percent, and 54 percent, respectively, whereas the corresponding results for non-participants are 66 percent, 84 percent, and 57 percent, indicating substantial economic inefficiencies among both groups of farmers. The hypothesis of equal technical and allocative efficiencies between the two groups of farmers could not be rejected implying that NEP did not impact on technical and allocative efficiency in the dry land zone. Apart from using homogenous technologies, the two groups do not have significantly different technical and allocative efficiencies. Therefore, apart from using homogenous technologies, the two groups do not have significantly different overall productive efficiencies, suggesting that NEP did not have a positive impact on productive efficiency in the dry land zone.

The results in both agro-climatic zones confirm that NEP has had no impact on the productive efficiencies of farmers. The empirical evidence regarding the influence of new technological interventions on technical efficiency is mixed. The positive impact of NEP on technical efficiency in the wet highland zone is in agreement with Seyoum et al. (1998) who found considerably higher technical efficiency of maize production among participants in the SG project compared with the non-participants in eastern Ethiopia. Taylor et al. (1986) also obtained a positive influence, though insignificant, of an agricultural credit program on technical efficiency of farmers in Brazil. On the contrary, Xu and Jeffrey (1998) obtained significantly lower technical efficiency for hybrid rice production in China as compared with conventional rice production while Singh et al. (2000) obtained lower technical efficiency for newly established Indian dairy processing plants after liberalization of the dairy industry compared to the old plants.

Table 5.7: Crop production efficiency distributions in Babile

	TE		AE		EE	
	Number of farmers (percent farmers)		Number of farmers (percent farmers)		Number of farmers (percent farmers)	
Level (percent)	Participants	Non-participants	Participants	Non-participants	Participants	Non-participants
<50	5(10)	8(16)	7(14)	-	14(28)	16(32)
51-60	4(8)	7(14)	1(2)	-	24(48)	15(31)
61-70	16(32)	12(25)	3(6)	3(6)	12(24)	3(6)
71-80	16(32)	9(18)	9(18)	6(12)	-	14(29)
81-90	9(18)	12(25)	23(46)	30(61)	-	1(2)
91-100	-	1(2)	7(14)	9(19)	-	-
Mean	68	66	81	84	54	57
Minimum	23	25	16	32	13	16
Maximum	88	92	99	98	68	88

Source: Own computation.

The negative impact of NEP on allocative efficiency in the wet highland zone is actually consistent with all the above studies. For example, Taylor et al. (1986) obtained a significant negative impact of an agricultural credit program in Brazil on allocative efficiency of participant farmers; Xu and Jeffrey (1998) also obtained significantly lower allocative efficiency for hybrid rice production in China as compared with conventional rice production across all the three regions studied; and Singh et al. (2000) obtained lower allocative efficiency for newly established Indian dairy processing plants after liberalization 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. Therefore, the negative (or lack of) impacts of new establishments and interventions on overall productive efficiency obtained in this and other studies are generally attributed to the considerably high allocative inefficiencies associated with new introductions. An extension service that is provided by small numbers of poorly trained staff with inadequate technical knowledge of either new technology or local innovative practices, in the face of growing numbers of farmers being encompassed in NEP over the years, coupled with poor credit, inefficient input supply systems, and lack of appropriate and adequate technology for most cereal crops

(Mulat, 1999), especially for the dry land zone, may hinder the effectiveness of NEP in promoting efficient food crop production.

5.4.2.2 Factors Influencing Farm Level Efficiency

The parameter estimates of the OLS regressions employed to identify the factors influencing farmers' levels of technical and allocative efficiencies in the respective districts are presented in Tables 5.8 and 5.9. For participant farmers in Meta, the results show that technical efficiency of participants is positively and significantly influenced by education, credit, previous participation in extension programs, and the share of the maize-potato system while their allocative efficiency is positively influenced by education, credit, and previous participation in extension programs.

Table 5.8: Determinants of production efficiency of farmers in Meta

Variable	Participants		Non-participants	
	TE	AE	TE	AE
Constant	1.211** (1.982)	0.231* (1.611)	0.523 (1.125)	0.125 (0.658)
AGE	-0.025 (-0.369)	-0.129 (-1.478)	0.036 (1.150)	0.063* (1.854)
EXTNSN	0.032 (1.021)	0.012 (0.055)	0.001 (0.667)	0.003 (0.656)
RWEDUC	0.183** (1.986)	0.088* (1.705)	0.058* (1.670)	0.063* (1.667)
PREDUC	0.021 (1.063)	0.101 (1.535)	0.011 (1.023)	0.028 (1.002)
FARMSZ	-0.321 (-1.012)	0.001 (0.002)	-0.014 (-0.101)	0.014 (1.023)
CREDIT	0.117** (2.116)	0.205** (2.189)	0.082* (1.635)	0.102* (1.852)
PARTCPN	0.201** (2.354)	0.091* (1.820)	0.087 (1.221)	0.033 (1.153)
LSTKUNT	0.01(0.985)	0.066 (1.033)	0.005 (0.036)	0.009 (0.786)
OFINCM	0.012 (1.01)	0.188 (0.963)	0.160 (1.185)	0.005 (1.001)
HHLABR	0.001 (0.687)	0.023 (0.990)	0.001 (0.855)	0.022 (0.881)
MZPOT	0.228 ** (2.132)	0.022 (1.021)	0.174 * (1.812)	0.029 (1.020)
MKTDIST	0.021 (1.212)	-0.034 (-1.425)	0.014 (1.127)	-0.071(-1.188)
R^2	0.72	0.54	0.53	0.51
F	5***	4***	6***	3***

Notes: *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level.
Figures in parentheses are t -ratios.

Source: Own computation.

The role of credit and education cannot be overemphasized in the effective functioning of NEP. The serious shortage of cash facing the farmers partly due to deteriorating product prices and the demands of new inputs for adequate knowledge of proper utilization have undesirable impact on timely farming operations and optimal input applications, thereby influencing farmers' levels of technical and allocative efficiencies (Ali and Byerlee, 1991; Assefa, 1995). Further, the positive and significant impact of previous participation in extension programs on technical and allocative efficiency confirms the important role of greater experience with new techniques of production in promoting farmers' technical and allocative efficiency under improved technology. This also implies that NEP is likely to enhance the technical and allocative efficiency of farmers in the long run as farmers fully respond to the new demands of the technologies and the program also begins to have better credit and input supply systems.

For non-participant farmers in Meta, the results show that technical efficiency is positively and significantly influenced by education, credit, and the share of the maize-potato system while their allocative efficiency is positively and significantly influenced by age, education, and credit, indicating that traditional farmers make better technical and allocative decisions if they acquire basic education, have greater experience with traditional technology, and have better access to credit. However, unlike in the case of the participants, previous participation in extension programs does not significantly influence the technical efficiency of non-participant farmers. This is mainly because these farmers have rarely benefited from extension programs in view of their poor access to sufficient amount of land to allocate for the application of new technology, poor awareness of the benefits of new technology, serious cash constraints to settle down payments for input credit, and their highly risk averse behavior (Assefa, 1995).

Furthermore, even when farmers happen to participate in previous programs, they do not seem to apply new methods and cultural practices they acquired through programs and projects to their own traditional crops in the subsequent years after 'graduation'. For instance, farmers destroyed soil conservation structures following the phasing out of projects and also continued planting traditional maize by broadcasting instead of planting in rows which they practiced while growing improved maize. They are generally little prepared to take advantage of new techniques learnt to improve their efficiency in traditional crops production, and neither could they continue using improved technology to improve their efficiency in food production due to the serious supply constraints especially of improved seeds which are only rationed through NEP (Mulat, 1999).

Farmers practicing the maize-potatoes cropping systems are also technically superior in view of more efficient use of land through appropriate intercropping. Although not significant, extension visits, household labor, primary education, off- farm income, and livestock ownership have a positive influence on technical and allocative efficiency of farmers in Meta. The mixed impact of market distance is not clear, however. While it has a negative impact on allocative efficiency as expected, its positive influence on technical efficiency in Meta is unexpected, however. Nevertheless, it has no significant impact either on technical or allocative efficiency partly because of little variation among the sample farmers in terms of distance from the district town in view of the homogeneity of the villages based on which they were selected.

Table 5.9: Determinants of production efficiency of farmers in Babile

Variable	Participants		Non-participants	
	TE	AE	TE	AE
Constant	2.195***(3.698)	2.103*** (5.223)	3.101*** (3.589)	1.523** (2.325)
AGE	0.029 (1.135)	0.071* (1.655)	0.044 (1.201)	0.102* (1.944)
EXTNSN	0.071 (1.178)	0.023 (1.02)	0.087 (1.457)	0.149 (1.052)
RWEDUC	0.095* (1.825)	0.108** (2.078)	0.067* (1.626)	0.121** (2.005)
PREDUC	0.132 (1.452)	0.021 (1.077)	0.021 (1.142)	0.022 (1.014)
FARMSZ	-0.028 (-1.014)	0.033 (1.025)	-0.014 (-0.101)	0.027 (1.110)
CREDIT	0.017 (0.116)	0.022 (1.350)	0.002 (0.833)	0.103 (1.425)
PARTCPN	0.037 (1.256)	0.049 (1.057)	0.087 (1.921)	0.009 (0.981)
LSTKUNT	-0.021 (-1.211)	0.038 (1.422)	-0.005 (-0.036)	0.004 (0.861)
OFINCM	0.128* (1.950)	0.092* (1.735)	0.260** (2.268)	0.092* (1.967)
HHLABR	0.092 (1.015)	0.025 (1.273)	0.113 (1.481)	0.002 (0.699)
CERPULS	0.119**(2.070)	0.002 (0.989)	0.233*** (3.568)	0.011 (1.089)
MKTDIST	-0.011 (-1.058)	-0.102 (-1.512)	-0.027 (-1.201)	-0.020 (-1.114)
R^2	0.61	0.57	0.56	0.49
F	10***	4.5**	7***	3.6**

Notes: *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level.
Figures in parentheses are t -ratios.

Source: Own computation.

For both participant and non-participant farmers in Babile, the results in Table 5.9 show that their technical efficiency is positively and significantly influenced by education, the share of the cereal-pulse system, and off-farm income, whereas their allocative efficiency is positively and significantly influenced by age, education and off-farm income. Although not significant, while previous participation in extension programs, credit, extension visits, and household labor have a positive influence, market distance has a negative influence on the technical and allocative efficiency of farmers in Babile. Although insignificant, livestock ownership negatively influences technical efficiency but has a positive impact on allocative efficiency. The negative influence on technical efficiency may be due to the competitive nature of crop and livestock production under conditions of serious feed shortages where farmers have to feed livestock through heavy thinning and defoliation (Storck et al., 1997) or have to travel long distances in search of feed, thereby delaying critical cropping operations. The positive influence on allocative efficiency may be due to the fact that the income generated from more livestock keeping activity helps relieve the liquidity constraints farmers face to acquire adequate amounts of inputs such as fertilizer at the right time.

The results also confirm that the cereal-pulse system in Babile offers opportunities for higher technical efficiency in crop production. This cropping system is mainly practiced to manage the risk of crop failure due to drought and to increase production per unit area through soil fertility improvement, better control of pests and diseases and more efficient use of land. Further, the results confirm the positive impact of off-farm income on technical and allocative efficiency in crop production probably through its influence on timely and adequate use of new inputs like fertilizer.

The available off-farm employment opportunities in Babile such as petty trade, charcoal selling, and food-for-work programs greatly relieve farmers' liquidity constraints enabling them to buy inputs such as fertilizer, to settle down payments for fertilizer acquired from NEP, and to acquire food during critical times of food shortage, thereby maintaining the productive capacity of the household (Bezabih, 2000). The significance of off-farm income as opposed to credit also confirms the critical shortage of both formal and informal credit in the area probably due to the low repayment capacity of farmers and the consequent loan defaults as a result of frequent crop failures.

5.4.3 Conclusions

The participant and non-participant farmers in the two agro-climatic zones have considerable overall productive inefficiencies, suggesting the existence of immense potentials for enhancing production through improvements in efficiency with available technology and resources. In the wet highland zone, the participants in the program used a superior technology and have higher technical but lower allocative efficiencies than the non-participant farmers, relative to their respective technologies, with the result that both groups exhibited greater and comparable overall productive inefficiencies. Therefore, the results show no evidence of impact of NEP on production efficiency in the wet highland zone. In the dry land zone, apart from using homogeneous technology, the two groups of farmers do not have significantly different technical and allocative efficiencies and hence they exhibit similar overall productive efficiencies. Therefore, NEP has had no positive impact on overall productive efficiency of farmers in the dry land zone. An investigation of the influence of several socio-economic and institutional factors on efficiency revealed that education, credit, previous participation in extension programs, off-farm income, and the share of the leading cropping system in each zone have a positive impact on efficiency.