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Determinants of efficiency of vegetable production in smallholder farms: The case of Ethiopia

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Abstract
Improving production efficiency remains as a plausible means of increasing productivity when resource reallocation, and the creation and adoption of new technologies are limited. Technical, allocative and economic efficiencies are derived from a sample of smallholder vegetable farmers in Ethiopia using parametric and non-parametric methods. The results reveal that the two methods yield similar estimates and the existence of substantial inefficiencies in production as well as efficiency differentials among farmers. The analysis of the determinants of efficiency of vegetable production using regression models show that low asset ownership, illiteracy, large family size, inadequate extension contacts, small farm size, age, low off/non-farm income and high consumer spending are the major socio-economic factors causing inefficiency of vegetable production in the study areas. A comparison of the market-driven (vegetables) with the whole-farm (crops and livestock) production efficiency indicates that lower economic efficiency scores for the former might be related to the limited access to capital markets, high consumer spending, and large family size.

Keywords: *Parametric and non-parametric methods, regression analyses, whole-farm versus enterprise, efficiency differentials, Ethiopia.*

Introduction

Ethiopia possesses a wide range of agro-ecological zones and diversified resources. Nearly all types of cereals, fibre crops, oil-seeds, coffee, tea, fruits and vegetables are grown. About 95% of the cultivated land is farmed by smallholders who mainly produce for subsistence needs, using low yielding traditional technologies with hardly any improved seeds and little fertiliser. Almost all of the estimated 1.4 million tonnes of fruits and vegetables is consumed locally and only 4.5% of the total production is exported. Even though there is a high demand at local and export markets, the contribution and performance of the horticultural sector to foreign earnings and as an income generating source for the farmers is minimal (only 1.1% of foreign earnings). Countries such as Kenya, which possess almost the same natural resources, are reaping much greater benefits (about 20%) from this sector (Anita & Andre, 2002).

Recent trends in agricultural policies of the government of Ethiopia prioritise exports and export-led growth (Amin, 2002). The promotion of selected agricultural products, particularly high value products with high export market potential is emphasized, e.g. coffee, cotton, fruits and vegetables, livestock and livestock products. In this attempt, improving production efficiency and the marketing systems of vegetables in the country in general, and the penetration of the prime market segment of Djibouti, in particular, is important.

In Africa, high population densities and the pressure on land resources together with the frequent crop and market failures have led to higher land use intensification as well as crop diversification (Arega, Manyong & Gockowski, 2006). For this reason, mono-cropping practices are being replaced by a diversified and complex intercropping system of annual food or cash crops or both, and perennial cash crops. In eastern Ethiopia where the population

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density is high, the main agricultural products are sorghum, maize, vegetables and *t'chat* (a mildly narcotic stimulant perennial crop). The intercropping of annual crops with perennial crops is about 41% according to Storck, Shimelis, Berhanu and Bezabih (1991). This has evolved in response to the growing pressure on land and agro-climatic risks. Vegetables and *t'chat* in the study areas are cash crop or market-driven farm products from which the income is mostly used to purchase farm inputs, livestock, and food during critical periods of the year. However, sorghum and maize are cultivated as the major staple food for the rural households.

In addition, income diversification between farm and off/non-farm activities is also practiced as a means to face these challenges. It may also be viewed as a response to poorly functioning capital markets: the cash from off/non-farm earnings can help stimulate farm investments and improve agricultural productivity (Haggblade, Hazzell & Brown, 1989; Hazzel & Hojjati, 1995). Given that poor households often lack access to non-farm income, imperfections in the labour market can contribute both to inefficient labour allocation in rural households and to a more unequal income distribution (Reardon, Delgado & Malton, 1992).

Efficiency is an important factor of productivity growth specifically in developing agricultural economies, where resources are meagre and opportunities for developing and adopting better technologies are limited. An empirical investigation of farm-specific efficiency helps determine, the level to which farmers use the existing technology, the level to which it is possible to raise output given the existing technology, and eventually whether it is possible to improve productivity by increasing efficiency with the existing technology.

Many performance evaluation studies in Ethiopia in particular, and other countries in general, have dealt exclusively with technical efficiency of production (Ajebifun, Battese & Daramola, 2002; Seyoum, Battese & Gleming, 1998; Abdul & White, 2000; Coelli & Battese, 1996; Getu, Storck, Belay & Vischt, 1998), which is only one aspect of efficiency of production. Many studies analysed the overall efficiency of production for major cereal crops (Arega & Reshid, 2005; and Coelli, Sandura & Colin, 2002), dairy farms (Bravo-Ureta & Reiger, 1991; and Johansson, 2006a) and for mixed farming systems (Bravo-Ureta & Pinheiro, 1997; Jema, forthcoming; and Arega et al., 2006). However, none of these studies analysed the efficiency of vegetable production in smallholder farming system, especially enterprise versus whole-farm. An evaluation of the economic performance of the market-driven farm products, particularly vegetables, is relevant because the impact of factor and product market performances might be considerable and these crops are produced under intensive cropping practices. Moreover, inputs are costly and vegetables are vulnerable to poor weather conditions and disease. Furthermore, vegetables are perishable products that require costly storage systems. Production costs are relatively high, compared to cereal crops. During dry seasons, considerable resources are devoted to irrigation practices. Farmers dig water wells up to 40 m deep manually and connect up to 10 diesel pumps to irrigate their farms from the near by lakes. A considerable amount of labour is also devoted to clearing water wells during wet seasons.

Given that little interest has been devoted to the performance assessment of the market-driven farm production in smallholder farms, this study aims to quantify and identify the determinants of technical, allocative and economic efficiencies of vegetable production. It uses the two frontier methods and compares it with the whole-farm (crops and livestock) production efficiency in two districts of eastern Ethiopia, (Haramaya and Kombolcha). Information about the overall efficiency of vegetable production and its determinants in these areas is important because these areas are major vegetable suppliers to the other parts of the country and to the Djibouti and Somalia markets, which account for approximately 79% of the vegetable exports.

The rest of the paper is organized as follows. Section 2 deals with the methodology. Section 3 deals with data and empirical models. Section 4 presents results and Section 5 concludes.

Methodology

Definition of technical and allocative efficiency

Modern efficiency measurement was established by Farrell (1957) who defines a simple measure of firm efficiency that could account for multiple inputs and multiple outputs. He proposed that the efficiency of a firm consists of two components: *technical efficiency*, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and *allocative efficiency*, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. The product of the two measures is *economic efficiency*, which could be defined as the ability of the firm to produce a well-specified output at minimum cost. More precisely, suppose we are given two inputs say X_1 and X_2 and the total output under the assumption of constant returns to scale (CRS). Consider Figure 1.

Knowledge of the unit isoquant of fully efficient units represented by SS' permits the measurement of

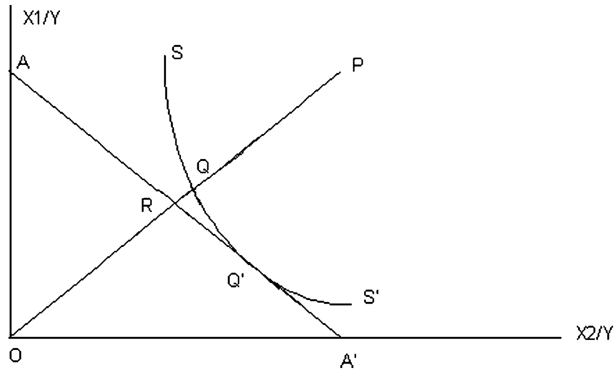

Figure 1. Input oriented measure of technical and allocative efficiencies for one output and two inputs. Source: Coelli, 1996, p. 4.

technical efficiency. If a given unit uses quantities of inputs defined by the point *P*, then distance *QP* represents technical inefficiency, which is the amount by which all inputs could be proportionally reduced without a reduction of the output level. It is usually expressed in percentage terms by the ratio $\frac{QP}{OP}$, which represents the percentage by which all inputs need to be reduced to achieve efficient production. Technical efficiency of the unit operating at is commonly measured by the ratio $\frac{OQ}{OP}$, which is equal to one minus $\frac{QP}{OP}$.

If the input price ratio represented by the slope of the isocost line *AA′* is also known, then allocative efficiency of the unit operating at *P* is defined to be the ratio $\frac{OR}{OQ}$. The distance *RQ* represents the reduction in production costs that would arise if production were to occur at the allocatively and technically efficient point *Q′*, instead of the technically efficient, but allocatively inefficient, point *Q*.

The total economic efficiency is defined as the ratio $\frac{OR}{OP}$ where the distance *RP* can also be interpreted in terms of cost reduction. It is the product of technical and allocative efficiency measures. Note that all these measures are bounded between zero and one.

2.2 Estimation methods

Farrell's (1957) original work has led to a number of efficiency measurement approaches. The two major approaches are the Stochastic Frontier (SF) approach proposed by Aigner, Lovell and Schmidt (1977); and Meeusen and Van den Broeck (1977) and the Data Envelopment Analysis (DEA) approach by Charnes, Cooper and Rhodes (1978). The strengths of the stochastic frontier approach are that it deals with the stochastic noise and permits statistical tests of hypotheses pertaining to the structure and the degree of inefficiency. Its main weakness is the assumption of an explicit functional form for the technology and frequently for the distribution of the inefficiency terms. However, the non-parametric method has some attractive features. It requires no specification of the functional form for the underlying technology, it can handle multiple outputs and inputs, it requires no judgment as to the relative importance of inputs and outputs, and it yields meaningful targets for improvement amongst inefficient Decision Making Units (DMUs). It is a relative measure. It solves a separate linear programme for each DMU searching for the linear combination of other DMUs that produce most outputs given the same or fewer inputs. Its drawback is that it is likely to be sensitive to measurement errors or other noises in the data because it attributes all the deviations from the frontier to inefficiencies.

The stochastic frontier method. The stochastic frontier production function for this study is specified as follows:

$$\ln Y_i = \beta_0 + \ln \sum_{j=1}^{5} \beta_j X_{ij} + e_i \tag{1}$$

where ln denotes the natural logarithm; i represents the *i*th farm in the sample; Y_i represents vegetable-farm revenue for the *i*th farmer; X_{ij} refers to the farm input variables of the *i*th farmer; $e_i = v_i - u_i$ is the residual random term composed of two elements: v_i and u_i. v_i is a symmetric component and permits for a random variation in output due to factors such as weather, omitted variables and other exogenous shocks. The other component u_i reflects the technical inefficiency relative to the stochastic frontier. The parameters, β, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma^2}$ of the above stochastic production function can be estimated using maximum-likelihood method, which is consistent and asymptotically efficient (Aigner et al., 1977).

The dual cost frontier of the production function in (1) is given by

$$\ln C_i = \alpha_0 + \left(\sum_{j=1}^{5} \alpha_j W_{ij}\right) + \alpha_6 Y_i^* \tag{2}$$

where *i* refers to the *i*th sample farm; C_i is the minimum cost of production; W_i are input prices; Y_i^* is the farm revenue adjusted for noise v_i; and αs are parameters.

Following Bravo-Ureta and Reiger (1991), and Kopp and Diewert (1982), for a given level of output

Y_i*, the technically efficient input vector of the ith firm, X_{it}, is derived by solving (2) and the observed input ratios $\frac{X_1}{X_i} = m_i (i > 1)$ simultaneously. Assuming the self-dual Cobb–Douglas production function, the dual cost frontier is derived algebraically and written in the following form:

$$C_i = C(W_i, Y_i^*; \alpha) \tag{3}$$

where C_i is the minimum cost of the ith farm associated with the adjusted revenue Y_i* and α is a vector of parameters to be estimated. The economically efficient input vector of the ith firm X_{ie}, is derived by applying Shepard's lemma and substituting the firm's input prices and adjusted output level into the resulting system of input demand equations

$$\frac{\partial C_i}{\partial W_n} = X_{ie}(W_i, Y_i^*; \alpha) \tag{4}$$

where n represents the total number of inputs used. The observed, technically and economically efficient costs of production of the ith firm are then equal to $W_i'X_i$, $W_i'X_{it}$ and $W_i'X_{ie}$, respectively. According to Sharma, Leung and Zaleski (1999) these cost measures are used to compute technical efficiency, $TE_i = \frac{W_i'X_{it}}{W_i'X_i}$, economic efficiency, $EE_i = \frac{W_i'X_{ie}}{W_i'X_i}$ and allocative efficiency, $AE_i = \frac{W_i'X_{ie}}{W_i'X_{it}}$ indices of the ith farm.

The DEA method. The input-oriented[1] constant returns to scale (CRS) DEA frontier for the calculation of technical efficiency (TE) is given by the solution to linear programmes of the form

$$\begin{gathered} \underset{\theta,\lambda}{Min}\,\theta \\ s.t - y_i + Y\lambda \geq 0, \\ \theta x_i - X\lambda \geq 0, \\ \lambda \geq 0 \end{gathered} \tag{5}$$

where x_i and y_i are input and output vectors of the ith farmer, respectively, X is an $m \times n$ input matrix and Y is an $s \times n$ output matrix representing data for all n farmers in the sample, θ is a scalar, and λ is an $n \times 1$ vector of constants. θ is always less than or equal to one. A value of one indicates a point on the frontier and hence the existence of a technically efficient farmer, according to Farrell's (1957) definition. The DEA model (5) has an intuitive interpretation. The problem takes the ith farmer and then seeks for the amount by which the input vector, x_i, can be reduced and still attain the same output level.

Assuming identical input prices,[2] economic efficiency[3] (EE) is simply obtained by solving the following DEA model:

$$\begin{gathered} \underset{\lambda,\theta_{EE}}{Min}\,\theta_{EE} \\ s.ty_i + Y\lambda \geq 0 \\ \theta_{EE}c_i - C\lambda \geq 0 \\ \lambda \geq 0 \end{gathered} \tag{6}$$

where c is a scalar representing cost or budget level, and C is a $1 \times n$ matrix of observed costs. Intuitively, the problem takes the ith farmer and then seeks for the amounts by which the input cost, c_i can be reduced and still remain on the production frontier.

Allocative efficiency (AE) is then given by

$$AE = \frac{EE}{TE} \tag{7}$$

The technical, allocative and economic efficiency scores are measured based on the above DEA models using General Algebraic Modelling System (GAMS).

Determinants of efficiency. Measurement of efficiency may not be an end by itself. More so, it reinforces the need to determine what factors influence efficiency. Hence, one can only overcome inefficiency by knowing what really causes it. The most commonly followed procedure is that the inefficiency or efficiency index is taken as a dependent variable and is then regressed against a number of other explanatory variables that are hypothesised to affect efficiency levels. However, a number of authors (e.g. Kumbhakar, Ghosh & McGuckin, 1991; Battese & Coelli, 1995) used a specific model that allows estimating efficiency scores and simultaneously tests the effect of explanatory variables noting that the two-stage testing procedures introduce some bias in estimation. Moreover, recent development in the non-parametric literature (Simar & Wilson, 2007) employed single and double bootstrapping methods by describing a coherent data-generating process (DGP) consistent with regression of DEA efficiency scores on some covariates in a second stage. This enabled them circumvent the problem related to the inherent dependency of the DEA efficiency estimates and make valid inference. In addition to this, Bravo-Ureta and Pinheiro (1993) argued that it may not be possible to identify all the factors affecting farm-specific efficiency, but only the most important socio-economic and demographic variables that are expected to influence farm-specific efficiency measures based on significance levels.

Technical, allocative and economic efficiency estimates derived from stochastic and DEA frontier models are regressed using OLS and Tobit models respectively, on the farm-specific explanatory variables that might explain variations in efficiency across farms. The rationale behind using the Tobit model for DEA efficiency scores is that some farms have an efficiency score of one and the bounded nature of efficiency between zero and one. In this case, the estimation with OLS would lead to biased parameter estimates (Greene, 1991). The Tobit results and the marginal effects for DEA estimates evaluated at sample means are presented in Table VIII.

Data

Sources and description of data

This study uses data from a survey conducted on 150 vegetable farmers of Haramaya and Kombolcha districts in eastern Ethiopia during the year 2003. A large set of annual data was obtained on production, consumption, socio-economic, and institutional constraints and conservation decision of the households. Data on most input prices were also collected from sample traders for two periods (wet season and dry season).

The major crops grown in these areas are vegetables, sorghum, maize and *t'chat*. Small-scale livestock and poultry production are also practiced. The most commonly grown vegetables include potato, onion, carrot, cabbage and beetroot. Vegetables and *t'chat* are considered as high value (market-driven) crops mainly produced for sale. Vegetables are usually grown on relational contract basis for wholesalers who in turn sell the produce to the vegetable exporters in the towns Diredawa and Kombolcha. The only vegetables consumed by households are those sorted out at the wholesale market and left unsold at the retail market.

A two-stage purposive sampling procedure was used to select vegetable growing Peasant Associations (PAs) in the first stage and vegetable growing farmers in the second stage. Next, a multi-stage proportional random sampling method was used to select 75 households from each district, thus 150 households were surveyed.

Description of the variables

The variables used in the SF, DEA, OLS and Tobit models are defined as follows:

i. Outputs: Physical yield of vegetables (potato, onion, carrot, cabbage and beetroot) all in kilograms.

ii. Inputs: Defined as the major inputs used in the production of vegetables in i, namely:

Land: Represents the physical unit of cultivated vegetable land in hectare.

Labour: Man-days converted into total hours worked, of family, exchange and hired labour used for land preparation, planting, weeding or cultivation, irrigation and harvesting.

Fertilizers: Includes total costs of organic, inorganic fertilizers (UREA and DAP) and pesticides used by the farm households.

Irrigation: Represents expenditures on irrigation during the survey year. It includes expenditures on renting, fuel, oil and lubricants for pumping sets.

Seeds: Represents the average market value of both local and improved vegetable seeds.

iii. Input prices: The input prices needed for deriving the dual cost frontier in the parametric method and for solving the cost minimizing DEA model in the non-parametric method are defined as follows. W_1 represents the annual land tax (Dollar/hectare). W_2 is the average wage paid for hired labour in these areas. Other variables are expressed in value terms and hence their prices were not computed.

iv. Efficiency factors: Denotes various farm-specific factors hypothesized[4] to explain differences in productive efficiency among farmers, namely:

Age: Represents the age of the household head in years.

Farm size: Defined as the total area of the cultivated vegetable land in hectare.

Fragmentation: Represents the number of farm plots owned by the household.

Education: It is a dummy variable defined as one if the household head attended at least one year of schooling and zero otherwise.

Off/non-farm income: Includes the off-farm income (off-farm labour wage) and the income from non-farm activities (retail trade, forest product trade and rural crafts). It is a dummy variable that is one if the household earns off/non-farm income and zero otherwise.

Credit: Includes access to credits for farm inputs and other farm activities from formal and informal sources. It is a dummy variable defined as one if the farmer had access to credit and zero otherwise.

Extension visits: Defined as the number of times the extension agent visited the farmer during the survey year.

Expenditures: Represents the total yearly expenditures of the household on goods and services (clothing, household goods, consumer goods, medical, schooling, political organizations and funeral).

Assets: Defined as the sum of current values of all furniture, farm implements, other equipment and livestock owned by the households.

Family size: Represents the total number of members of the household.

Farm distance: Defined as the distance of the farm from the house of the household head in kilometres.

Descriptive statistics of the input-output variables used in efficiency estimation and the socio-economic and institutional variables that are hypothesised to affect efficiency levels are provided in Table I.

Table I. Descriptive statistics of input-output variables and efficiency factors.[5]

Input-output variables	Mean (SD)	Efficiency factors	Mean (SD)
Land (hectare)	0.58 (0.58)	Age (years)	34.00 (10.21)
Irrigation (Dollar)	93.94 (182.53)	Family size (persons)	7.00 (2.33)
Labour (h)	483.60 (436.85)	Fragmentation (number of plots)	1.81 (1.12)
Fertilizer (Dollar)	35.22 (54.49)	Farm-size (hectare)	0.58 (0.58)
Seed (Dollar)	73.84 (94.38)	Assets (Dollar)	1429.66 (10726.26)
Potato (kg)	3158.00 (7661.89)	Expenditures (Dollar)	281.73 (225.91)
Onion (kg)	449.67 (893.97)	Extension visits (number)	1.65 (2.51)
Carrot (kg)	409.13 (658.53)	Farm distance (km)	1.02 (1.07)
Cabbage (kg)	523.67 (717.53)	Education (literate/illiterate)	0.60 (0.99)
Beetroot (kg)	538.50 (1188.40)	Off/non-farm income (yes/no)	0.21 (0.41)
		Credit access (yes/no)	0.39 (0.49)

Source: Field survey data, 2003.

Empirical results

Stochastic frontier estimates

The maximum-likelihood estimates of the parameters of the Cobb–Douglas Stochastic frontier production function are obtained using a computer programme FRONTIER 4.1 (Coelli, 1994). The results are presented in Table II. The signs for the slope coefficients of the stochastic production frontier are all positive, as expected. Except for the coefficients for fertilizers and seeds, the other coefficients are all significant at the 1% level suggesting that the model fits the data well. Fertilizers and seeds are insignificant may be because there was a limited application of these inputs because they are costly. High elasticities of output to irrigation (0.534) suggest that vegetable production is very sensitive to irrigation. The statistically significant estimate for the variance parameter, γ, is an indication that the technical inefficiency effects affect output. The estimated value of σ^2 is also significant at 5% level, which means that the conventional average production function is not an adequate representation of the data.

The dual frontier cost function, derived analytically from the stochastic production frontier given in Table II is as follows:

$$\begin{aligned}\ln C_i = & -2.240 + 0.210\ln W_{i1} + 0.490\ln W_{i2} \\ & +0.233\ln W_{i3} + 0.060\ln W_{i4} \\ & +0.006\ln W_{i5} + 0.917\, Y_i^* \end{aligned} \quad (8)$$

The average TE, AE and EE estimates obtained using SF approach are respectively 0.68, 0.65 and 0.43, which reveals the existence of a substantial inefficiency of vegetable production in the study areas. Moreover, TE, AE and EE indices of most of the farmers fall within the ranges 0.70 – 0.80, 0.80 – 0.90 and 0.40 – 0.50 respectively. An allocative efficiency of 0.65 indicates that if these farmers operate at full allocative efficiency levels, they could reduce, on average, their costs of production (or the cost of the purchased inputs) by 35% and produce

Table II. OLS and ML estimate of the average production function and the Cobb–Douglas stochastic frontier production function, respectively.

Variable	Parameter	OLS estimates Coefficient (standard error)	ML estimates Coefficient (standard error)
Constant	β_0	3.147*** (0.526)	3.585*** (0.420)
Land	β_1	0.237*** (0.081)	0.229*** (0.080)
Irrigation	β_2	0.549*** (0.096)	0.534*** (0.085)
Labor	β_3	0.244*** (0.082)	0.254*** (0.067)
Fertilizers	β_4	0.059 (0.059)	0.066 (0.057)
Seeds	β_5	0.011 (0.065)	0.007 (0.060)
R^2		0.797	
γ			0.239 ** (0.125)
σ^2			1.060 ** (0.567)
λ			1.060 ** (0.567)
Log likelihood			−140

*Significant at 10% level; **significant at 5% level; ***significant at 1% level.

the same level of output. If we consider physical outputs per se, these farmers may increase their production on average by 32% if they are able to acquire the necessary technical and managerial skills.

DEA frontier estimates

DEA models are estimated for the same number of farms, input-output variables as for the stochastic frontier using GAMS. The estimated technical efficiencies differ substantially among farmers, ranging from 0.02 to 1.00 with 41 fully efficient farmers out of the 150 sampled farmers. The average technical efficiency score amounts to 0.66. Even though the maximum and the minimum technical efficiency scores differ considerably, the modal technical efficiency class is $0.90-1.00$ with a reasonable spread near the range.

The mean allocative efficiency score amounts to 0.64 with only seven fully efficient farmers. When allocative and technical efficiencies were combined to compute economic (cost) efficiency measure, the average economic efficiency score with seven fully efficient farmers was found to be 0.43. The economic efficiencies of most of farmers are observed to lie within a range of 0.20 to 0.50 and economic efficiency differentials among the farmers of the two districts are observed. The mean economic efficiencies are 0.46 for Haramaya and 0.39 for Kombolcha.

Comparison of the efficiency estimates from the two approaches

The frequency distribution of technical, allocative and economic efficiency estimates obtained from SF and DEA models are presented in Table III. The average technical and allocative efficiency scores obtained using DEA models are slightly lower than the efficiency scores obtained using SF models. A number of studies have compared the efficiency estimates derived from SF and DEA models and found mixed results. The results obtained in this study are well in line with the results obtained by Ferrier and Lovell (1990), Sharma et al. (1999), Drake and Weyman-Jones (1996), and Johansson (2006b). The result of this study is also consistent with the argument that the stochastic models account for the influence of factors beyond the control of the firms, which would otherwise be attributed to inefficiency in the DEA models. Moreover, the DEA efficiency measures exhibit greater variability than the SF efficiency measures. The Pearson and Spearman rank correlation coefficients between the efficiency scores obtained from SF and DEA approaches are reported in Table IV. The results show that they are highly positively correlated, which means that the two approaches are comparable. Moreover, the results from both models indicate the existence of substantial inefficiencies of vegetable production in the study areas, which in turn means that there are considerable opportunities to increase agricultural output without supplying additional inputs, given the existing technology.

Technical and allocative efficiency estimates obtained from the two approaches are in conformity with the results obtained by Arega and Reshid (2005), and Coelli and Battese (1996). However, economic efficiency estimates are low compared to the results obtained by Arega and Reshid (2005), and Coelli and Battese (1996), but in line with the results obtained by Abay and Assefa (1996), Weir (1999). The economic efficiency estimates are higher than the results obtained by Hussain (1989);

Table III. Distribution of technical, allocative and economic efficiencies obtained from parametric and non-parametric methods.

	Parametric methods			Non-parametric methods		
Efficiency	TE	AE	EE	TE	AE	EE
≥0.90 ≤1.00	–	19	–	45	21	14
≥0.80 <0.90	15	26	–	12	17	1
≥0.70 <0.80	60	24	3	10	23	6
≥0.60 <0.70	49	21	11	14	32	12
≥0.50 <0.60	20	17	35	25	24	12
≥0.40 <0.50	8	18	42	21	13	29
≥0.30 <0.40	2	20	29	12	12	24
≥0.20 <0.30	1	6	26	8	5	30
≥0.10 <0.20	–	–	4	2	3	20
≥0 <0.10	–	–	–	1	–	2
Mean	0.68	0.65	0.43	0.66	0.64	0.43
Std dev	0.10	0.20	0.13	0.26	0.21	0.24
Minimum	0.26	0.23	0.15	0.20	0.10	0.20
Maximum	0.89	0.98	0.75	1.00	1.00	1.00

Table IV. Pearson's and Spearman rank correlation coefficients obtained from SF and DEA models.

Efficiency	Pearson	Spearman
TE	0.65	0.93
AE	0.72	0.98
EE	0.67	0.95

Bravo-Ureta and Pinheiro (1997); and Bravo-Ureta and Evenson (1994).

Robustness of the DEA efficiency estimates

Since DEA attributes all the deviations from the frontier to inefficiency, it is likely to be sensitive to the input-output outliers. The tests for the sensitivity of DEA efficiency scores to input-output outliers are, therefore, crucial to verify the robustness of the efficiency results.

To examine the sensitivity of DEA efficiency estimates to the presence of outliers, we followed a procedure used, among others, by Resti (1997). After solving the DEA problems using all the observations composing the sample, all vegetable farmers that are fully efficient were deleted and DEA problems were solved once more on the new sample. The correlation between the efficiency scores obtained on the original and the reduced sample is an indication of the robustness of the results. The Pearson's and Spearman rank correlation coefficients were then estimated to detect the sensitivity of DEA efficiency scores to the input-output outliers. The results are provided in Table IV.

The Pearson's and Spearman rank correlation coefficients between technical, allocative and economic efficiency scores on the original and the reduced sample are positive and high, which demonstrates the robustness of the efficiency estimates obtained in this study.

Efficiency comparison based on managerial practices

An attempt is also made to categorize farmers into two groups based on the type of vegetables they grow. Group 1 refers to those growing vegetables that are less demanding in terms of managerial practices " the less managerially demanding" vegetables (potato, carrot and beetroot). Group 2 refers to farmers growing vegetables that are more demanding in terms of managerial practices "the more managerially demanding" vegetables (onion, cabbage and group 1 vegetables). Of the 150 sampled farmers, 58 fall in group 1 and 92 fall in group 2. The classification is made on the basis of the interviews made with the farmers on the input requirements, sensitivity to unfavourable weather conditions and disease, and the number of harvest in a given year (Table VI). About 87% of the respondents reported that, compared with group 2, group 1 vegetables does not require much fertile soil, seeds are relatively cheaper and some can be duplicated on the farm, and are superior in tolerating bad weather and disease. About 92% of the respondents reported that group 1 vegetables require less cultivation and weeding. Moreover, the average number of times group 1 vegetables were harvested during the survey year, 2.3, is higher than the average number of harvest for all vegetables (1.8). For the stochastic frontier estimates, the average technical, allocative and economic efficiencies for group 1 are found to be lower than the corresponding estimates of group 2. In the DEA estimates, the average technical and economic efficiencies for group 1 are found to be lower whereas allocative efficiency is higher than the corresponding estimates of group 2 (Table VII). Even though higher technical, allocative and economic efficiencies are expected for farmers in group 1 than for farmers in group 2, the results show that this is only true for allocative efficiency indices from the DEA models. For the former result, it seems that the diversification effect outweighed the effects of differences in managerial practices. These results may also indicate a self-selection effect that farmers with higher managerial skills choose to grow the more managerially demanding vegetables, although they are not securing any higher traditional efficiency measures.

Table V. Sensitivity of DEA efficiency scores to input-output outliers.

Description	TE	AE	EE
Number of fully efficient farmers	41	7	7
Pearson's correlation coefficient	0.75	0.71	0.90
Spearman rank correlation coefficient	0.81	0.98	0.97

Table VI. Farmers response to the classification of vegetables in groups 1 and 2 based on different variables.

	Percentage of farmers	
Variable	Group 1	Group 2
Tolerance to bad weather and disease	87	13
Cheaper seeds	82	18
Seed duplication on the farm	88	12
Does not require much fertile soil	91	9
Less cultivation and weeding	92	8
Average number of harvest per year	2.3	1.8

Table VII. Average technical, allocative and economic efficiencies of vegetable farmers in groups 1 and 2.

Efficiency	Group1	Group 2
TE_{SF}	0.65	0.70
AE_{SF}	0.62	0.66
EE_{SF}	0.39	0.45
TE_{DEA}	0.58	0.71
AE_{DEA}	0.65	0.63
EE_{DEA}	0.36	0.46

Determinants of efficiency of vegetable production

The results obtained from the first stage estimations indicate that the average efficiency scores are low and that there are efficiency variations among farmers. To explain these variations, regression analyses are made. The model estimates from Tobit and the marginal effects (evaluated at the sample means) for the DEA estimates are presented in Table VIII. The regression results from the two models reveal that extension visits and assets positively and significantly affect technical efficiency whereas farm size, consumption expenditures and family size have a significant negative effect. The factors that positively and significantly affect allocative efficiency of vegetable production are education, off/non-farm income, credit, assets and extension visits, whereas age, consumption expenditures and family size appear to have a significant negative effect. Assets and extension visits significantly and positively affect economic efficiency whereas family size and consumption expenditures have a significant negative effect.

The negative effect of farm size on technical efficiency, as found in the studies by Coelli et al. (2002) and Getachew (1995) could partly be related to small farm size. A larger farm size is expected to yield a significant positive effect on efficiency levels because such farms realise increasing returns to scale (Coelli et al., 2002). Regarding family size, the fact that off/non-farm job opportunities are rare and unattractive, and a weak negative correlation (−0.04) of family size with farm size might have resulted in the under-employment of the labour force in the household, which in turn results in a negative relationship with efficiency. The statistically significant negative signs on the estimated coefficients on all efficiency scores for the consumption expenditures may reveal a situation where households that spend excessively on consumption goods are unable to support their agricultural activities and, therefore, become less efficient.

Table VIII. Factors affecting TE, AE and EE of smallholder vegetable farmers in eastern Ethiopia.[6]

	TE		AE		EE	
Variables	Coefficient (std error)	Marginal effect	Coefficient (std error)	Marginal effect	Coefficient (std error)	Marginal effect
Intercept	0.862 (0.143)***	0.708	0.831 (0.098)***	0.797	0.599 (0.099)***	0. 538
Age	−0.0008 (0.003)	−0.0006	−0.004 (0.002)**	−0.004	−0.0008 (0.003)	0.0003
Farm size	−0.043 (0.016)***	−0.035	0.004 (0.010)	0.004	−0.015 (0.014)	−0.041
Fragmentation	−0.029 (0.020)	−0.023	0.013 (0.014)	0.012	−0.011 (0.020)	−0.006
Education	0.099 (0.056)*	0.081	0.069 (0.038)*	0.066	0.036 (0.056)	0.028
Off/non-farm inc	0.007 (0.063)	0.006	0.079 (0.043)*	0.075	0.058 (0.043)	0.009
Credit	−0.018 (0.051)	−0.015	0.067 (0.035)**	0.064	0.036 (0.035)	0.054
Extension visits	0.029 (0.010)***	0.024	0.003 (0.007)*	0.003	0.016 (0.007)**	0.016
Expenditures	−0.0003 (0.0001)***	−0.0002	−0.00007 (0.00007)*	−0.00007	−0.0002 (0.0007)**	−0.0002
Asset	0.00003 (0.00005)***	0.00003	0.00006 (0.00003)*	0.00006	0.00002 (0.00003)***	0.00002
Family size	−0.023 (0.012)**	−0.017	−0.012 (0.008)***	−0.019	−0.021 (0.012)**	−0.019
Farm distance	−0.020 (0.023)	−0.019	−0.019 (0.015)	−0.018	−0.002 (0.016)	−0. 012
Log L		−51.10		17.7		16.7

*significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table IX. A comparison of whole-farm and vegetable-farm efficiency measures and their determinants.

	Whole-farm	Vegetable-farm
Variables	Non-parametric	Non-parametric
TE	0.87[a]	0.66
AE	0.61	0.64
EE	0.53	0.43
Asset	+All[b]	+All
Consumption expenditures	−AE	−All
Education	Not sig.	+TE, AE
Farm size	−All	−TE
Age	Not sig.	−AE
Off/non-farm income	+TE	+AE
Extension visit	−TE	+All
Family size	−TE	−All
Credit	Not sig.	+AE
Diversification	−AE, EE	Not sig.

[a]TE and EE estimates reported in Table IX are slightly lower whereas AE is slightly higher than those reported by Jema (forthcoming). This is because (in the estimation of efficiency scores for vegetable production) some inputs and outputs were merged to overcome the methodological drawbacks of DEA when many variables are used. The analysis of the whole-farm efficiency was carried out again using the reduced number of variables to compare vegetables and whole-farm efficiency meaningfully.
[b]"+All" implies that the indicated efficiency factor affects all the efficiency scores positively and significantly and "−All" implies that the indicated efficiency factor affects all efficiency scores negatively and significantly.

The result obtained regarding off/non-farm income might be explained by the fact that off/non-farm employment may absorb underemployed labour resources, improve the experience and human capital of the farm operator, bring additional income that may contribute towards funding farm activities and improve managerial skills, and therefore, result in a positive relationship with allocative efficiency. The negative effect of age on allocative efficiency might be because older farmers are less concerned with adapting new practices, acquiring and analyzing information, resulting in a negative coefficient.

The marginal effect (0.024) of extension visits for technical efficiency shows that, for the sample period, an increase in the extension visit by one led, on average, to an increase in technical efficiency by 0.024. For the dummy variable credit, if a farmer has access to credit, for example, his allocative efficiency score will increase on average by 0.064.

Whole-farm versus enterprise level (Vegetable-farm) efficiency

Farmers in the study areas do not only grow vegetables, but are rather mixed-crop farmers who mainly produce vegetables for sale. Jema (forthcoming) conducted a whole-farm efficiency analysis of these farm households and found a higher TE and EE scores, but lower AE scores (TE = 0.91, AE = 0.60 and EE = 0.56). It is important to identify why such a high level of economic inefficiency of production appears at the enterprise level (vegetable-farm) production compared to the whole-farm. In the shift from whole-farm to enterprise level efficiency analysis, there might be technological as well as risk differentials. Different technologies use different resource combinations. The combination of these farm-specific resources may affect to what extent a given technology is appropriate for a specific enterprise or for the whole-farm. New technologies can represent new managerial practices, a modification of current practices, or simply a refinement of the current technologies. A lower economic efficiency of vegetable production may be attributable to the managerial challenge that the farm operator faces due to either the intensive production practices or the imperfections in the product or factor markets or both, and financial markets. Market imperfections commonly occur in rural markets in developing countries and they are characterized by substantial transaction costs and imperfect information (Hoff, Braverman & Stiglitz, 1993; de Janvry, Fafchamps & Sadoulet, 1991). This occurrence may cause farm households to be only partially integrated into the commercial markets and a differential between buying and selling prices emerges. The presence or absence of market imperfections may have efficiency implications (Stein, Bekele & Pender, 2001). Vegetable farmers in these areas rely completely on the wholesalers stationed in Diredawa and Kombolcha for all the services and may have weak bargaining power in negotiating prices or the quantity to be marketed. This difficulty is further aggravated by their frequent dependence on the wholesalers for advance payments and the provision of packing materials and transport. The competition at the wholesalers and exporters level is limited owing to the existence of a few actors who may create barriers to the entry of other traders. A similar condition prevails in the factor markets as well. This imperfection in the product or factor markets or both, as well as capital markets may contribute to the higher economic inefficiency of the market-driven farm production. Regression results also show that accesses to capital markets positively and significantly affect the allocative efficiency of the market-driven farm production. This result suggests that farmers devote much of the funds they receive from credit and income from off/non-farm activities to the market-driven farm production. Extension visits are shown to significantly and negatively affect the whole-farm efficiency but significantly and positively affect the enterprise level efficiency. This finding indicates that extension agents mainly focus on the market-driven farm production and provide less attention to the whole-farm production. The effect of consumption expenditures is high for the market-driven farm production compared to production for subsistence purposes, as expected. Age significantly and negatively affects allocative efficiency of vegetable production, but is insignificant for the whole-farm efficiency of production. This result further indicates that the market-driven farm production requires the ability to manage resources efficiently, the ability to adapt to new practices and to acquire and analyse information, which may not be easily realised during the later ages of one's life. Crop-diversification significantly and negatively affects AE and EE of the overall production but does not significantly affect the efficiency of vegetable production. Family size significantly and negatively affects all efficiency scores for vegetable production, but only affects technical efficiency of the overall production. The reverse is true for farm size.

Concluding remarks

This study uses stochastic and DEA frontier methods to measure technical, allocative and economic efficiencies of vegetable production in two districts of eastern Ethiopia using detailed survey data from 150 farmers distributed over nine PAs, in the year 2003. The results yielded mean technical, allocative and economic efficiencies of 68%, 65% and 43% for the parametric methods and 66%, 64% and 43% for non-parametric methods (Table III). The Spearman rank correlation coefficients indicate that the two methods are similar. Moreover, the lower TE and AE indices for the DEA method are consistent with the theory that DEA attributes all the deviations from the frontier to inefficiencies. Results from both methods indicate the existence of substantial technical, allocative and economic inefficiencies as well as efficiency differentials among individual farmers. Furthermore, an economic efficiency index of 43% indicates that the total cost of input use of the sampled farmers could be decreased by 57% while they still produce the same level of output. Accordingly, current levels of output may be substantially increased if greater effort is directed towards improving farmers' efficiency by reallocation of the existing resources rather than being restricted to creating or transferring new technologies or both.

This study identifies assets, education, family size, extension visits, farm size, age, and off/non-farm income and consumption expenditures as major factors causing inefficiency of vegetable production in these areas. A comparison of the market-driven (vegetables) with the whole-farm indicates that lower economic efficiency scores for the market-driven farm production might be related to access to capital markets, high consumer spending, imperfections in the factor and product markets, and large family size.

Consequently, the results suggest that to improve efficiency of vegetable production in the study areas, policy makers should focus on raising farmer's education, farm asset formation, providing efficient saving mechanisms, credit and extension services. Such measures may, in turn, reduce the food security problem and support the export-led growth policy in the country by enhancing productivity.

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Notes

1. The input-oriented and output-oriented efficiency measures will coincide when the technology exhibits CRS, but are likely to differ otherwise. In this study, an input-oriented efficiency measure is used because input quantities appear to be primary decision variables for most of the farmers. Moreover, this choice is not expected to considerably affect the result because farmers in the sample operate small farms and hence the technology is unlikely to be substantially affected by variable returns to scale (Coelli et al., 2002).
2. Input price variation is observed across districts, PAs and households with in the PAs. This could be a seasonal effect or a differential in access to input markets. Since it seems unlikely that input price variation would reflect differences in resource availability across households, the average input prices were chosen as a measure of resource scarcity for each farm households.
3. The standard measure of economic efficiency which is obtained in two stages: first by estimating the minimum price-adjusted resource usage given technological constraints, and secondly by comparing this minimum to the actual or observed costs will be reduced to the DEA problem (6) with the assumption of identical prices.
4. First, a Tobit model was fitted to technical, allocative and economic efficiencies using a constant and 18 variables and a restricted model was fitted by excluding 7 variables (experience, plot ownership, crop diversification, market distance, extension distance, road distance and district) that were not individually statistically significant in the model. The log-likelihood functions for the unrestricted and restricted models were calculated for the technical, allocative and economic efficiencies. A likelihood ratio test was performed for testing the null-hypotheses that all the seven coefficients are zero and could not be rejected at the 1% significance level. Hence the analysis of the data proceeded by using the 11 restricted variables defined above.

5. Descriptive statistics of input-output variables and efficiency factors for the whole-farm are found in the paper by Jema (forthcoming).
6. Only regression results obtained using DEA efficiency scores is presented because of the high correlation between SFA and DEA efficiency scores.

References

Abbay, A., & Assefa, A. (1996).The impact of education on allocative and technical efficiency of farmers: The case of Ethiopian smallholders *Ethiopian Journal of Economics*, *5*(1).

Abdul, W., & White, B. (2000).Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods *Applied Economics*, *32*.

Aigner, D., & Lovell, C., & Schmidt, P. (1977).Formulation and estimation of stochastic frontier production function models *Journal of Econometrics*, *6*.

Ajibefun, I. A., & Battese, G. E., & Daramola, A. G. (2002).Determinants of technical efficiency in smallholder for crop farming: Application of stochastic frontier production function *Quarterly Journal of International Agriculture*, *41*.

Amin, A. (2002). Agriculture Development-led Industrialization and Export-led Growth: compatibility analysis. A paper submitted to EEA for the first international conference on Ethiopian Economy. Addis Ababa.

Anita, S., & Andre de J. (2002). Review of the impact of changes in EU pesticides legislation (directive 2000/42/EG) on fresh food exports from developing countries into the EU. Case study: The horticulture export centre in Ethiopia.

Arega, D. A., & Rashid, M. H. (2005).The efficiency of traditional and hybrid maize production in eastern Ethiopia: An extended efficiency decomposition approach *Journal of African Economies*, *15*.

Arega, D. A, Manyong, V. M., & Gockowski, J. (2006). The production efficiency of intercropping annual and perennial crops in southern Ethiopia: A comparison of distance functions and production frontiers. *Agricultural Systems*, *91*, 51–70.

Battese, G. E., & Coelli, T. J. (1995).A model for technical inefficiency effects in a stochastic frontier production function for panel data *Empirical Economics*, *20*.

Bravo-Ureta, B. E., & Reiger, L. (1991).Dairy farm efficiency measurement using stochastic frontiers and neo-classical duality *American Journal of Agricultural Economics*, *73*.

Bravo-Ureta, B. E., & Pinheiro, A. E. (1993).Efficiency analysis of developing country agriculture: A review of the frontier function literature *Agricultural Resource Economics Review*, *22*.

Bravo-Ureta, B. E., & Pinheiro, A. E. (1997). Technical, economic, and allocative efficiency in peasant farming: Evidence from the Dominican Republic. *The Developing Economies, XXXV*-1, 48–67.

Bravo-Ureta, B. E., & Evenson, R.E. (1994).Efficiency in agricultural production: The case of peasant farmers in Paraguay *Agricultural Economics*, *10*(1).

Charnes, A., & Cooper, W., & Rhodes, E. (1978).Measuring the efficiency of decision-making units *European Journal of Operational Research*, *2*.

Coelli, T. J. (1994). A guide to FRONTIER version 4.1: a computer program for stochastic frontier production and cost function estimation. Armidale, Australia: Department of Econometrics, University of New England.

Coelli, T. J. (1996). A guide to DEAP version 2.1: a data envelopment analysis computer program. Working Paper 96/08. Armidale, Australia: Department of Econometrics, University of New England.

Coelli, T. J., & Battese, G. E. (1996).Identification of factors which influence the technical inefficiency of Indian farmers *Australian Journal of Agricultural Economics*, *40*.

Coelli, T. J, & Sandura, R., & Colin, T. (2002).Technical, allocative, cost and scale in Bangladesh rice production: A non-parametric approach *Journal of Agricultural Economics*, *53*.

de Janvry, A., & Fafchamps, M., & Sadoulet, E. (1991).Peasant household behavior with missing markets: some paradoxes explained *Economic Journal*, *101*.

Drake, L., & Weyman-Jones, T. G. (1996).Productive and allocative inefficiencies in UK building societies: a comparison of nonparametric and stochastic frontier techniques *Manchester School*, *64*.

Farrell, M. J. (1957).The measurement of productive efficiency *Journal of Royal Statistical Society*, *120*.

Ferrier, G. D., & Lovell, C. A. K. (1990).Measuring cost efficiency in banking: econometric and linear programming evidence *Journal of Econometrics*, *46*.

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). Kiel, Germany: Wissenschaftsverlag Vauk.

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*.

Greene, W. (1991). *LIMDEP: User's manual and reference guide.* New York: Econometric Software, Inc.

Haggblade, S., & Hazzel, P., & Brown, J. (1989).Farm-nonfarm linkages in rural Sub-Saharan Africa *World Development*, *17*.

Hazell, P. B., & Hojjati, B. (1995).Farm/non-farm growth linkages in Zambia *Journal of African Economies*, *3*.

Hoff, K., Braverman, A., & Stiglitz, J. (1993). *The economics of rural organization: Theory, practice, and policy*. Oxford: Oxford University Press.

Hussain, S. (1989). *Analysis of economic efficiency in northern Pakistan: Estimation, causes and policy implications*. Ph.D. Dissertation. University of Illinois.

Jema, H. (forthcoming). Production efficiency of smallholders' vegetable-dominated mixed farming systems in eastern Ethiopia: a non-parametric approach. *Journal of African Economies,*

Johansson, H. (2006a). The input and output economic efficiency aspects of profit maximization: the case of Swedish dairy farms. Swedish University of Agricultural Sciences (SLU). Working paper series 2006:3, Uppsala.

Johansson, H. (2006b). Mathematical and econometric approaches to technical efficiency estimation-How sensitive are the efficiency scores to the methodology choices and functional forms? Swedish University of Agricultural Sciences (SLU). Working paper series 2006:2, Uppsala.

Kopp, R. J., & Diewert, W. E. (1982).The decomposition of frontier cost functions deviations into measures of technical and allocative efficiency *Journal of Econometrics*, *19*.

Kumbhakar, S. C., & Ghosh, S., & McGuckin, J. T. (1991).A generalized production frontier approach for estimating determinants of inefficiency in U.S. dairy farms *Journal of Business and Economic Statistics*, *9*.

Reardon, T., & Delgado, C., & Malton, P. (1992).Determinants and effects of income diversification amongst farm households in Burkina Faso *Journal of Development Studies*, *28*.

Meeusen, W., & van den Broeck, J. (1977).Efficiency estimation from Cobb-Douglas production functions with composed errors *International Economic Review*, *18*.

Resti, A. (1997).Evaluating the cost-efficiency of the Italian banking system: What can be learned from the joined application of parametric and non-parametric techniques *Journal of Banking and Finance*, *2*.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*, 31–64.

Seyoum, E. T., & Battese, G. E., & Fleming, E. M. (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*.

Sharma, K. R., & Leung, P., & Zaleski, H. M. (1999).Technical, allocative and economic efficiencies in swine production in Hawaii: a comparison of parametric and non-parametric approaches *Agricultural Economics*, *20*.

Stein, H., & Bekele, S., & Pender, J. (2001). *Market imperfections and land productivity in the Ethiopian highlands*.

Storck, H., Shimelis, W., Berhanu, A., & Bezabih, E. (1991). The role of perennial and vegetable crops in the farming system of individual peasants in the Hararghie highlands. *Acta Horticulturae 270*. Economics in Developing Countries I.

Weir, S. (1999). *The effects of education on farmer productivity in Ethiopia. Working paper series, No. 7. Centre for the Study of African economies*. University of Oxford: Oxford.