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EVALUATING THE EFFICIENCY OF FARMERS IN ETHIOPIA

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tAj/roc/j 7ta ur/fc'A? It ^rrmorjA *concerned with applying* Alta Emt/qpmen/ *Analysis (DEA) for* me-tzsurmg fAc *efficiency* 1.7 *.imAi/derv* fn *^Mapia r^tj wiMx* •*mLrf* muc&fc, *Constant-re*jaFrar-*to-scale* 'CRS'.' am/ I irraA/L'-reni^*s-to-scale* fl ^.Sy. ara *app/wd w individual /arm tevd* ITiz^.y-sci*tional* ^Awn^w/Arec *villages in Ethmp/u. 7he fjrrpfrreuJ* rera/tf r// AqfA weajitfw yA^n- /An/ rfe /awflerr-. .vj *the sample* /fc #/(w *technically* ı-w/Ae/L'n/ /Aad jcufe //icA/r^Hf *This implies that policy sho*UJiJ *largely* /XM5 <J« WreiWCY d/ FUiWJ£ *technical* //i'.. «rc} \/ufWIIT //k1 FI'J H^.T d^D J/Jifil 1J/1' 7^/ /AiTt' CJ FC^ki/M?/ tWrti/JHH in /At' ^L'/ «/■^1,/r7/4. ..Jggi' W.'^ -. Al .'JVi /JyAt I JirfL'^X'ntoFJ AdAi'd Off /Ar *specific* VttVJFOfMrttfM/

1. INTRODUCTION

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There are many rcastuis for nieasuring cfJkitw_v !'irs1. eftlciene} measures help idcntily relatively efficient units and give an estimate of ihc potential for resource cunserv^tion and/'or output increases of Lhe incl licicnt ones are improved. I roin an applied perspective, therefore, measuring efficiency is important us tins is the first step in a process that might lead to substantial resource savings .

Second, these resource savings have impuriant implications for both policy lormulation and firm management. Moreover, it is only by measuring efficiency and separating ns L-ilccts from the elfocis of the production cm ironmen! one can explore hypotheses concerning the sources of etTicicnuy ditfcrcnliae. Identi fical ion ıı‹ rl icsc source\ is essential lu lhe inslitutfon of public and private pnheics designed 10 increase the output of a limi hy simply increasing its efficiencies, without absorbing furl her resource's.

t hird, lhe benefits that could be reaped from the reulfocaiion of resnurccs from the less elficicnt areas to those that are efficient are immense for a demlopmg ecuHomy. These benefits are more pronounced for Llhmpian agriculture where there is very little room, at the moment to expand the sector through extensive use of land [1 4]j.

The investigation of the structure of production frontiers and measurement of production efficiency relative to these frontiers required modifying the conventional econometric techniques. New approaches have been developed that have raised the level of analysis and broadened the range of efficiency hypotheses that can be formulated and tested. For the last two decades, two quite different methodologies have been extensively used for determining efficiency frontiers, and the nature, existence, and magnitude of departures from the frontiers. These are: (a) econometric estimation of production functions; and (b) Data Envelopment Analysis (DEA) which is a version of mathematical programming.

Notwithstanding the ample work on the causes of the poor performance of Ethiopian agriculture, most of which identified policy failure as the major reason, very little attention was given to a systematic analysis of the efficiency of resource use in the small-scale peasant sector. In addition, few of the available studies on efficiency have centred on imperfect and partial measures of productivity such as yield per hectare and output per unit of labour. Only recently have some attempts been made towards systematic evaluation of the efficiency of farmers in Ethiopia. (see e.g. [1], [2], [3], [5], [10]). Yet, all of these studies used econometrics to measure efficiency.

This study attempts to apply DEA on farm level data from Ethiopia, and tries to investigate the existence, nature and extent of production inefficiency of these farms. The rest of the paper is organised as follows. The next section gives an overview of the basic conceptual framework used in the study and briefly comments on the major approaches to measuring efficiency. Section three presents a cursory review of the DEA models applied in this study. Section four discusses the sources and nature of the data, and explains the variables used in measuring the efficiency of the farmers. Section five provides with a discussion of the empirical results. Finally conclusions are drawn.

2. BASIC CONCEPTUAL FRAMEWORK AND APPROACHES TO MEASURING EFFICIENCY

Various definitions of technical efficiency have been forwarded. The most formal and notable definition of technical efficiency was given by Koopmans [21]. Accordingly, a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. Thus, a technically inefficient producer could produce the same output with less of at least one input, or could use the same inputs to produce more output. The various approaches to measuring efficiency are generally in line with this basic concept.

The classical approach to measuring efficiency is invariably attributed to the seminal paper by Farrell [15]. He suggested that we could usefully measure technical efficiency of a firm in terms of observed deviations from an idealised frontier or isoquant. His approach provided a theoretical basis for redirecting attention from the traditional average response production functions based on least squares estimates specifically to the deviations from that function, and for respecifying the regression and the techniques accordingly. Figure 1 is adapted from Battese [9] to illustrate Farrell's basic idea.

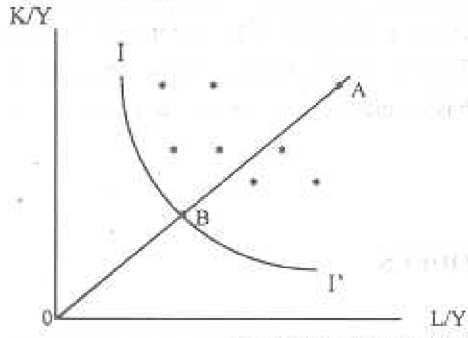

Fig. 1 Technical efficiency of firms in relative input space

Given a production function with constant returns to scale, Farrell [15] assumed that observed input-per-unit-of-output values for firms would be above the so-called *unit isoquant, II'*. Figure 1 depicts the situation in which firms use two inputs of production, K and L, to produce their output, Y, such that the points, defined by the input-per-unit-of-output ratios, (K/Y, L/Y), are above the unit isoquant. The unit isoquant defines the input-per-unit-of-output ratios associated with the *most efficient* use of the inputs to produce the output involved. The deviation of observed input-per-unit-of-output ratios from the unit isoquant was considered to be associated with *technical inefficiency* of the firms involved. He then defined the ratio, OB/OA, to be the *technical efficiency* of the firm with input-per-unit-of-output values at point A. The same could have been illustrated using production frontier (see Battese [9]).

The Farrell approach can be considered as a deterministic, non-parametric frontier approach. Frontier approaches refer to the concept of the production frontier as being the upper bound of the feasible region of production, i.e., the production function represents the maximum level of output that is technically feasible. These approaches focus on estimating the parameters of a production function where the production function is a true frontier of technically feasible production. Two major variants of frontier approaches can be distinguished, namely, Deterministic and Stochastic[2].

On the other hand, based on the estimation procedure adopted, the approaches to measuring efficiency can also be classified as: (a) econometric, which attempts to distinguish the effects of noise from the effects of inefficiency, and (b) mathematical programming, which lumps noise and inefficiency together and calls the combination 'inefficiency'. The econometric approach is parametric and confounds the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency, while the latter approach is non parametric and less prone to this type of specification error[3]. Indeed, some progress is underway to make the programming approach stochastic and the econometric approach more flexible in its parametric structure.

3. THE DEA MODELS

Farrell's traditional concept of technical efficiency can be applied to firms only when they aim at a single goal, and cannot be used when they seek to satisfy multiple goals. His approach was later generalised by Charnes, Cooper, and Rhodes [12] to multiple outputs, and was reformulated as a mathematical programming approach to efficiency measurement thereafter known as Data Envelopment Analysis (DEA). In this approach, the initial task is to determine a set of decision-making units (DMUs), as represented by observed data, that form an empirical production function or envelopment surface.

Then, DEA provides a comprehensive analysis of relative efficiency for multiple input-multiple output situations by evaluating *each* DMU and measuring its performance relative to the envelopment surface composed of other DMUs[4]. In other words, the efficiency of a given unit is measured *relative* to the efficiency of all other units subject to the restriction that all units lie on or below the frontier. Thereafter, units that lie on the surface are deemed 'efficient' as per the DEA terminology.

Different varieties of DEA models can be identified based on their orientations. On the one hand, models may focus on increasing, decreasing or constant returns to scale; on the other hand, they may determine an efficient frontier which may be piecewise linear, piecewise log-linear or piecewise Cobb-Douglas. Still another, they may utilise Archimedian or non-Archimedian constructs. Above all, models may aim at either input saving or output augmenting, or both.

The input-saving measure shows how large a proportion of the observed input would have been necessary for the output quantity observed if the unit in question had been moved to the efficient frontier. The output-increasing efficiency measure compares the actual output produced to that of a unit at a point on the production frontier that uses the same amount of inputs. Note that this study produces only the output-augmenting efficiency measures.

As yet, while the envelopment surfaces are identical for both input and output orientation, an efficient DMU is projected to different points on the envelopment surface based on the focus of orientation, i.e., according to whether or not the emphasis is on conservation of resources (input reduction) or maximising productivity (output augmentation)[5].

The traditional DEA model of Charnes, Cooper and Rhodes (CCR) [12] imposes three restrictions on the frontier technology prior to solving the envelopment problem, namely, constant returns to scale, strong disposability of inputs and outputs, and convexity of the set of feasible input-output combinations. The (output-oriented) DEA envelopment problem constitutes in solving the following linear programme:

$$\max_{\theta,\lambda} \theta \quad \text{..(1)}$$

subject to:

$$X\lambda \leq X_k$$
$$\theta Y_k \leq Y\lambda$$
$$\lambda, \theta \geq 0$$

Where, X is an n by N input matrix with columns Xi;
Y is an m by N output matrix with columns Yi;
λ is an N by 1 vector of weights to be attached to the sample firms for construction of an efficient firm ;
k denotes the DMU under investigation;
i=1,...,N indexes DMUs;
n is the number of inputs;
m is the number of outputs; and
θ represents the output-oriented measure of technical efficiency.

Solving (1) amounts to maximising the efficiency of the unit k subject to the efficiencies of all units in the set having an upper bound of one. The key feature of the model is that the weight vector, λ, is treated as unknown, and is chosen so as to maximise the efficiency of the target unit, k. The efficiency of the target unit, k, will either equal one in which case it is efficient relative to the other units, or will be less than one in which case it is inefficient. The values of the weight would of course generally differ from unit to unit.
The solution value, θ^*, gives the maximum possible output expansion for the firm k under consideration within the production possibility set for a given input level. The reciprocal of θ^* gives the (output-oriented) efficiency measure, i.e., $TEi=1/\theta^*$, for firm k. Problem (1) is solved N times, once for each producer being evaluated, to generate N optimal values of (θ,λ) and efficiency measures for each firm in the sample. The mean efficiency, i.e., E(TEi), gives a picture of the overall performance of the sample.

The type of reference technology assumed is important for the efficiency distribution obtained. By introducing restrictions on the sum of intensity weights (λ), DEA can accommodate different varieties of returns to scale. Banker [6] introduced the idea that the sum of the intensity variables in the DEA model can be used to identify the type of returns to scale[6]. The variable returns-to-scale variant of this problem introduced by Banker, Charnes, and Cooper (BCC) [7] can be modelled simply by adding to (1) the constraint[7]:

$$\mathbf{e}'\lambda = 1 \quad \text{...(2)}$$
where **e** is an N by 1 unit vector.

The technical efficiency measures corresponding to both constant returns to scale (CRS) and variable returns to scale (VRS) can be established by solving problem (1) both without and with the constraint (2) respectively. The consequence of the constraint (2), i.e., $\sum \lambda_i = 1$, on the distinction between the two models (CCR and BCC) is that the former measures the aggregate efficiency (i.e., purely technical and scale efficiency) while the latter yields a measure only of purely technical efficiency.

When the reference technology exhibits VRS, a need for a measure of scale efficiency arises. The two models can then be used to determine the scale efficiency of a unit. The scale efficiency (SE) of a unit (see, [7]) is the ratio of its CRS efficiency to its VRS efficiency. Scale inefficiency can be due to either decreasing or increasing returns to scale. Where CRS do not prevail, units can be compared given their scale of operations, or at least it would be informative to know the extent to which any inefficiency is the consequence of their scale of operations. In such cases, the overall or aggregate efficiency of a unit can be decomposed into its 'pure technical' and 'scale' efficiency. Such a decomposition has important policy implications since the two types of inefficiency do not call for the same type of cure. To illustrate these concepts, consider Fig.2.

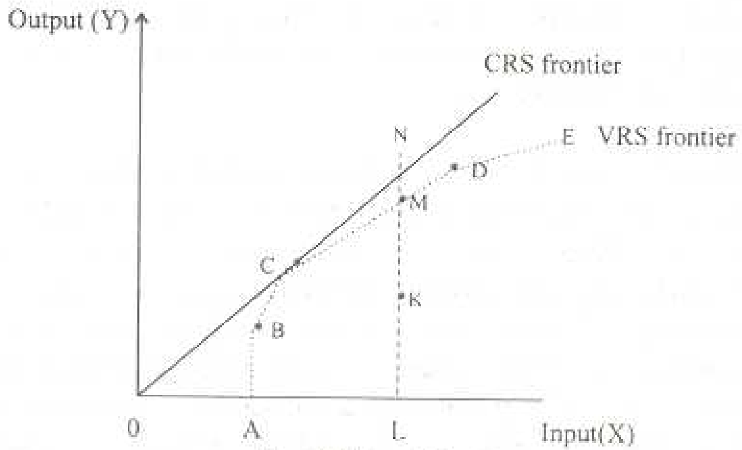

Fig 2 DEA-based frontier and efficiency measures

The figure depicts the production possibility set for the input-output mix (X,Y), where X is a vector of inputs and Y is a vector of output levels. The dotted curve ABCDE is the boundary of the production set (or it can be considered as the best practice frontier with VRS), while the thick ray from the origin through point C is the CRS frontier. Similarly, the frontier with non-increasing returns to scale is given by OCDE. The measure of inefficiency of observation K, which is inefficient, for its given scale of operations, can be obtained if it is compared to observation M which has the same input levels as K but is efficient.

The ratio LK/LM, which is the ratio of observed output to potential frontier output for given inputs, measures the level of pure (output-augmenting) technical efficiency of K. A measure of the (output-oriented) aggregate technical and scale efficiency of K is given if it is compared to C (or N) both of which have the largest average productivity (and C, being within the production set, is said to have the most productive scale size (MPSS)). Hence, the aggregate efficiency of K is given by the ratio LK/LN. The CCR and BCC models can then be used to determine the scale efficiency of a unit, which is measured by the ratio of aggregate efficiency and pure technical efficiency, i.e., LM/LN.

We can see from the figure (Fig. 2) that the (output-oriented) efficiency ratings as given by VRS are always higher than that of the CRS due to the additional constraint in the former. But, for the input-saving case, the former is lower. In general, of course, the input and output measures of scale efficiency do not coincide. This is due to the fact that the two measures yield different results towards the VRS model.

The CCR model can also be used to characterise the 'local' returns to scale *for a given unit*. A unit will be operating at decreasing returns to scale (DRS), at increasing returns to scale (IRS), or at the most productive scale size (MPSS) if the sum of λ^* at the optimal solution to (1) is greater than, less than, or equal to one, respectively. If IRS prevails at a point, then it is intuitive that average productivity (Y/X) would increase with increasing scale size, i.e., for greater values of X. In the same manner, if DRS prevails locally, the average productivity can be increased with smaller scale size, i.e., units with DRS are encouraged to decrease their activities rather than increase them. This implies that if a point is at MPSS, and hence maximises average productivity, then constant returns to scale (CRS) must prevail locally at that point.

Thus, IRS corresponds to the production possibility being less than MPSS (i.e., to the left of point C in Fig. 2), and DRS corresponds to the production possibility being greater than MPSS (i.e., to the right of point C in Fig.2). This characterisation of the optimal frontier into the three parts can also be carried out for the VRS model[8]. Information as to whether a unit is operating at increasing or decreasing returns to scale can prove useful in indicating potential redistribution of resources. For one thing, resources might be transferred from units operating at DRS to those operating at IRS to increase average productivity at both sets of units.

DEA is a programming approach. As such, it has an advantage since it is non parametric, i.e., it does not use any algebraic form for the frontier. Nor does it assume an inefficiency distribution, and hence it is deterministic. Moreover, the DEA approach, with its various extensions, provides a number of alternative ways to measuring efficiency. To begin with, the way the production frontier is constructed has some merits, for the DEA frontier envelops the data set in a better way than most econometric models do. Furthermore, subject to certain assumptions about the structure of the production technology, it envelops the data as tightly as possible. It is observed that, in some other respects as well, DEA appears to be a robust procedure for efficient frontier estimation [23].

The DEA has also provided new insights and additional information that is not available in the econometric methods. The empirical orientation and the absence of a priori assumptions of DEA proved particularly adept at uncovering some relationships that remained hidden from other methodologies, notably the comparison of returns to scale. In this connection, it is shown that DEA outperforms the stochastic frontier functions when it comes to estimating scale efficiency and determining the most efficient scale [18]. On the other hand, while DEA is relatively insensitive to model specification, it can be sensitive to variable selection and data errors, and is therefore usually criticised on statistical grounds. The empirical results of this study should be looked against this shortcoming of the DEA approach.

3. DATA AND VARIABLES

The data used in this study are from the first round of the Ethiopian Rural Household Survey which has been conducted by the Department of Economics, Addis Ababa University, in collaboration with the Center for the Study of African Economies, Oxford University. In the first round of the survey, the International Food Policy Research Institute (IFPRI) participated in collecting data in the seven of the fourteen villages. The project is an integrated rural household survey covering different aspects of the activities of rural households. In selecting the villages, emphasis was given to capture different types of farming systems and to incorporate the different agro-ecological regions of the country. All the villages are peasant associations (PAs) and the sampled households are randomly selected from them such that the number of sampled households in each PA is proportional to the population size of each *Woreda* (sub-district) in which the respective PAs are found. The survey covered in the first round a total of about 1500 households, and has generated a unique data set that will help in understanding the rural economy, enhance research on agriculture and help policy analysis in Ethiopia.

Data from only three PAs, Turufe Kechema (near the town of Shashemene), Sirbana Godeti (near the town of Debre Zeit), and Aze Deboa (near the town of Durame, Kambata) is used. Most of the annual, perennial and permanent crops that grow all over the country are grown in one or more of the villages[9]. The majority of the farmers in these villages use fertilizer, with the exception of Aze Deboa where the amount of fertiliser used is not significant. It was asserted that farmers in Shoa use relatively higher amount of fertiliser than farmers in the rest of the country [22].

The prominent crops grown in the three villages include: *teff*, barely, wheat, maize, sorghum, millet, potatoes, linseed, coffee, *chat*, *enset*, *gesho*, banana, eucalyptus tree and tobacco. Smaller number of observations are used than those included in the original data due to the removal of observations with missing values for some of the variables included in the study. This resulted in a sample size of 93 for Turufe Kechema, 81 for Sirbana Godeti and 74 for Aze Deboa, giving a total of 248 observations.

Because of the widely used practice of mixed farming in Ethiopia, the value of production for all crops grown in the 1994 *Meher* (main farming season in Ethiopia) is considered as the dependent variable. Only aggregate data (for all crops) on the input variables are available[10]. The non-marketed produce is valued at prices received for marketed surplus. Four inputs are used: land, labour, fertiliser, and a proxy for draft animals (total value of cattle). The land variable includes the total amount of land (in hectares) that is used for cropping in the *Meher* season of the same year. Labour is measured in man-days and includes all categories of labour spent in the major farming activities, i.e., ploughing, weeding and harvesting. The total value of fertiliser (in Birr) is taken as fertiliser input. Since the amount of draft animals is not included explicitly in the data, the total value of cattle owned (in Birr)[11] is used as a proxy. A summary of some of the descriptive statistics on output and input variables is presented in Table 1.

Table 1: Summary of Descriptive Statistics on Output and Input Variables

Variable	Sample mean	Sample std. error	Minimum value	Maximum value
Value of output (Birr)				
Turufe Kechema	1916.47	1748.04	10.00	7722.50
Sirbana Godeti	3284.67	2086.76	10.00	9931.00
Aze Deboa	539.97	506.75	10.00	3504.00
Land (hectare)				
Turufe Kechema	1.09	0.94	0.06	7.00
Sirbana Godeti	1.07	0.61	0.25	3.25
Aze Deboa	0.69	0.33	0.25	1.75
Labour (man-days)				
Turufe Kechema	179.08	316.98	10.00	1942.50
Sirbana Godeti	814.49	742.44	11.00	3891.00
Aze Deboa	97.24	129.97	11.00	761.00
Fertiliser (Birr)				
Turufe Kechema	134.66	124.98	10.00	645.00
Sirbana Godeti	191.40	150.16	10.00	700.00
Aze Deboa	46.03	44.16	4.00	200.00
Cattle (Birr)				
Turufe Kechema	934.06	979.06	17.00	4402.00
Sirbana Godeti	836.23	908.32	12.00	3341.00
Aze Deboa	948.34	564.78	20.00	2673.00

Source: Ethiopia Rural Household Survey Data

A close examination of Table 1 reveals that the mean of both input and output is the highest in Sirbana Godeti (except for land and cattle). Apparently, this is because farmers in this area are surplus producers and suppliers of one of the most important cash crops, *teff*, and the village is located in Ada *Woreda* that is known for its best quality *teff*. Apart from this, Ada, near Addis Ababa, has the most urbanised and commercial environment of all cereal producing villages in the country. Data on all variables (except cattle) confirm that Aze Deboa is by far the poorest of all the sites. This area is occasionally hit by famine and it is one of the most densely populated areas of the country. Farmers in this area largely depend on permanent crops and are known to migrate for occasional employment to other parts of the country as a result of population pressure.

We can see from Table 1 that Sirbana Godeti has the highest standard deviation on all variables except land and cattle (the variability in land and cattle being the highest in Turufe Kechema). Perhaps, partly this is owing to the great discrepancy among the farmers in the village. On the other hand, this discrepancy is moderate in Aze Deboa which, by and large, consists of poor, and mostly, subsistent farmers. Another aspect of this table which needs closer attention is that of land. We observe farmers who own as much as 7 hectares while the amount of official land holding is barely greater than or equal to two hectares, on average. This is not surprising since, in the analysis, all land that is cultivated during the season is included, and it is evident that some farmers rent in land from other households informally through fixed rental arrangements or share cropping.

5. EMPIRICAL RESULTS

The output-oriented technical efficiency estimates are calculated for the three villages separately[12]. The two variants of DEA are applied, one with constant returns to scale and another with variable returns to scale. Table 2 presents the mean technical efficiencies of the farmers for both CRS and VRS together with the number of farmers falling in each category of returns to scale. The table also presents the mean scale efficiency scores.

The mean technical efficiency estimated for each village (CRS) shows that the farmers involved are highly technically inefficient (0.44, 0.39, and 0.40 for Turufe Kechema, Sirbana Godeti and Aze Deboa, respectively). This indicates that the outputs for the average farmer in each village could have been increased by more than 50% had the CRS frontier technology been employed. The VRS estimation also produced similar results, except that smaller gains are obtained in comparison to the CRS ones, as it should be. Other studies also showed that Ethiopian farmers are characterised by high level of technical inefficiency. A study also arrived at the same conclusion using a different data set for Ethiopian farmers [10][13]. The results (both CRS and VRS) also indicate that farmers in Turufe Kechema are, on average, more efficient than farmers in the other two villages since the mean technical efficiency is the highest for Turufe Kechema.

Table 2: Mean Technical and Scale Efficiency Estimates

Turufe Kechema

	ORS (m=43)	CRS (n=14)	DRS (n=36)	All Observations
CRS	0.40	0.71	0.38	0.44
VRS	0.55	0.71	0.54	0.57
Scale efficiency	0.81	1.00	0.73	0.81

Sirbana Godeti

	IRS (n=12)	CRS (n=24)	DRS (n=45)	All observations
CRS	0.37	0.46	0.35	0.39
VRS	0.63	0.46	0.53	0.52
Scale efficiency	0.63	1.00	0.67	0.76

Aze Deboa

	IRS (n=50)	CRS (n=8)	DRS (n=16)	All observations
CRS	0.34	0.73	0.40	0.40
VRS	0.42	0.73	0.46	0.46
Scale efficiency	0.87	1.00	0.88	0.88

Source: Own Manipulations.

* n=number of observations in each category.

At this juncture, it seems appropriate, once again, to stress one important merit of DEA. Unlike the econometric approaches, it enables comparison of some production characteristics of units, particularly the analysis of the level of scale efficiency and local returns to scale[14]. When we examine the scale properties of the farmers, we find from Table 2 that a large proportion of farmers in Sirbana Godeti are operating under DRS and are less efficient than those operating under IRS. Hence, it seems that for these farmers technical inefficiency arises due to DRS.

But note that about 70% of the farmers in Aze Deboa are operating under IRS. This indicates that most of the farmers in Aze Deboa are too small as it is evident from their low levels of inputs (Table 1). The reason may be intensive population pressure on land in Aze Deboa. This latter argument can also be applied for Turufe Kechema where most farmers are also operating under IRS and where population pressure is relatively higher than Sirbana Godeti, though lower than that of Aze Deboa. Despite this similarity between Tururfe Kechema and Aze Deboa, those farmers in Turufe Kechema operating under IRS are more technically and generally efficient than those operating under DRS. The opposite is the case for farmers in Aze Deboa, i.e., the main source of inefficiency seems to be IRS.

Table 3: Percentages of Technical Efficiency Estimates

Range	CRS			VRS		
	Turufe Kechema	Sirbana Godeti	Aze Deboa	Turufe Kechema	Sirbana Godeti	Aze Deboa
≤ 0.09	5,4	9,9	9,5	3,2	7,4	5,4
0.10-0.19	9,7	7,4	27,0	5,4	1,2	24,3
0.20-0.29	21,5	18,5	10,8	15,1	9,9	10,8
0.30-0.39	17,2	21,0	13,5	13,9	14,8	14,9
0.40-0.49	13,9	13,6	6,8	10,8	17,3	6,8
0.50-0.59	9,7	12,3	6,7	9,7	12,4	2,7
0.60-0.69	6,5	7,4	4,1	8,6	9,8	5,4
0.70-0.79	3,2	2,5	6,7	2,1	8,7	9,4
0.80-0.89	4,3	3,7	6,8	4,3	4,9	4,1
≥ 0.90	8,6	3,7	8,1	26,9	13,6	16,2

Source: Own manipulation

Turning to the scale efficiency measures. Table 2 depicts that the level of scale efficiency of the farmers in the three Villages is higher than their technical efficiency. Thus, there is obviously no sever scale efficiency problem. In other words, technical inefficiency accounts for the largest potential of efficiency improvement. The level of scale efficiency for all the farmers is low in Sirbana Godeti is the lowest (0.76) compared to the other two villages (0.81 and 0.88, respectively, for Turufe Kechema and Aze Deboa). Also the scale efficiency estimates for Sirbana Godeti, for both local IRS and DRS, are lower than the other two villages.

An important question, however, pertains to whether scale inefficiency is due to IRS or DRS. In Turufe Kechema, the larger proportion of scale inefficiency seems to be due to DRS than IRS. The converse is true for Sirbana Godeti. But for Aze Deboa, it seems that both IRS and DRS have equal contribution to scale inefficiency[15].

More information can be obtained about the distribution of the alternative efficiency measures if we examine Table 3 which presents DEA-based technical efficiency scores in terms of the percentages of occurrences of technical efficiency in different ranges. For instance, it is apparent from the table that the proportion of farmers with a score of technical efficiency less than 50% (CRS) for the three villages is 68%, 70% and 68%, respectively, for Turufe Kechema, Sirbana Godeti and Aze Deboa.

6. CONCLUSIONS

This study had, as its central theme, the task of applying the DEA approach to measuring efficiency. To this effect, the two commonly used techniques of DEA, i.e., the original CRS and its extension, VRS, were applied to agricultural data from Ethiopia. By far the most important finding of the study is that the two alternative DEA models of measuring technical efficiency generate about the same conclusion, namely, that inefficiency is one of the main characteristics of agricultural production for the sampled farmers. This shows that there is a great potential for increasing the efficiency of these farmers, given the available resources and technology.

In addition, it was attempted to investigate the scale efficiencies of the farmers in the sample, and was found that inefficiency in their scale of operations contribute to the overall inefficiency, though they seem to be relatively more scale efficient than they are purely technically efficient. The over-riding message for policy formulation is that more benefits could be tapped from implementing strategies of enhancing their level of technical efficiency Another caveat that would impinge on policy is the spatial variation in the level of efficiency, a fact which implies selective adoption of policy according to the environment.

Finally, this exercise points to avenues of future research in at least two directions. First, the study is likely to provoke further research that incorporates the peculiar characteristics of small-holder agriculture in Ethiopia, notably risk and uncertainty. In a similar vein, the factors which contribute to high inefficiency of production for these farmers and the main sources of regional efficiency variations remain to be investigated, and the conclusion of this study should stimulate further research in this respect.

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Notes

1. Lecturer, Department of Economics, Addis Ababa University, P.O.Box 1176, Addis Ababa Ethiopia.

2. For more details, see [17].

3. For more details, see [17]. Applications of DEA in the measurement of efficiency are now abundant. For a more extensive bibliography of DEA studies, see [24].

4. An important difference between stochastic and DEA is that while the former optimises across all firms, DEA optimises on each firm using a series of optimisations. An important caution is in order concerning DEA as a measure of efficiency. Since DEA yields relative efficiency measures and defines a unit as inefficient by comparing combinations of input and output with other units, units operating with input-output quantities sufficiently far from the other units at both ends of the size distribution may be identified as efficient for the sheer reason of the lack of comparable units. Problems of this kind are, however, minimal if the sample size is large in comparison to the number of inputs and outputs, which is the case in this study. This is because larger

samples decrease the average level of efficiency due to the positive probability of including more efficient outliers in the sample.

5. For constant returns to scale, the input-oriented and the output-oriented efficiency measures are identical. Moreover, it is straight forward to obtain an input-oriented envelopment problem by replacing problem (1) with its dual minimisation problem.

6. The concept of returns to scale as used in DEA is that of multiple output case unlike the conventional single output definition of the concept. For more details, refer to [8].

7. Note that the type of technology assumed in problem (1) is constant returns to scale.

8. The convexity of the VRS frontier ensures that IRS will be more frequent at smaller units.

9. All the three villages are located in the former Shoa province (Aze Deboa and Turufe Kechema, Southern Shoa, and Sirbana Godeti, Eastern Shoa). Two of them, Turufe Kechema and Sirbana Godeti, are in region 4, while Aze Deboa is in the Southern region.

10. All the variables are for the last four months of *Meher* season.

11. Since other modern inputs such as HYVs and herbicides are used to an even lesser extent, the results should not be biased by the exclusion of these inputs.

12. The DEA estimation was programmed in Gauss 3.2.

13. The mean efficiency scores in this study are very low, even worse than the stochastic results of the same data set [2]. This is not surprising since DEA technical efficiency estimates are biased down-wards due to the fact that DEA lumps the effects of measurement error and any other external factors to inefficiency. This only shows that great care has to be taken when using DEA to analyse agricultural production units in LDCs like Ethiopia where there is high degree of uncertainty and risk.

14. Because the hypothesis that farmers in the sample operate under constant returns to scale was tested formally using an F-test for a restricted model and the results indicated that constant returns to scale can not be rejected at 5% level of significance.

15. Asmerom and David [4] argue that a l4arge proportion of farmers in Northwest and Central Ethiopia (not using fertiliser) are too small.

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