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By

Gelan, Ayele and Muriithi, Beatrice

Conference paper, The 3rd Conference of African Association of Agricultural Economists Africa and the Global Food and Financial Crises 19 - 23 September 2010, Cape Town, South Africa at The Westin Grand Cape Town Arabella Quays

Measuring and Explaining Technical Efficiency of Dairy Farms: A Case Study of Smallholder Farms in East Africa

Ayele Gelan[1] and Beatrice Muriithi
Market Opportunities Theme
International Livestock Research Institute

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Abstract: *This paper measures and explains technical efficiency of 371 dairy farms located in seventeen districts in East African Countries. Four output and nine input types were used to calculate the efficiency scores for each farm. A two-stage analysis was conducted to measure and explain the efficiency scores. First, the efficiency scores were measured by using a data envelopment analysis (DEA) approach which was implemented with a linear programming method. About 18% of the farms were fully productive, each with efficiency scores of unity, which meant this group is currently operating on the production possibility frontier. On the other hand, about 32% of the farms have efficiency scores below 0.25, which means about a third of the dairy farms would need to expand dairy production by at least 75% from the current level without any increase in the level of inputs. Second, a fractional regression method was used to explain the efficiency scores by relating then to a range of explanatory variables. The findings indicate that technology adoption factors such as the existence of improved breeds; feed and fodder innovations (e.g. growing legumes) have positive and statistically significant effects on the level of efficiency. Similarly, zero-grazing seem have positive and highly significant effects. As far as marketing variables are concerned, interestingly selling milk to individual consumers or organizations seems to contribute to dairy efficiency positively and significantly than other marketing outlets such as traders of chilling plants. Membership of dairy cooperative has a positive effect but this is not statistically significant.*

Key words: Dairy farms; efficiency scores; Data Envelopment Analysis; fractional regression; returns to scale.

[1] Corresponding author: Market Opportunities Theme, International Livestock Research Institute
P.O. Box 30709-00100, Nairobi, Kenya, Tel: +254-20-4223411, +254 721 770 679 (Mobile), Fax: +254-20-4223394; email:<a.gelan@cgiar.org.

1 INTRODUCTION

Economic performance indicators play an important role informing resource allocation decisions by producers, policy-makers and donors. In order to alleviate poverty and improve the livelihoods of smallholder farms particularly in Sub-Saharan Africa, policy-maker and donors often design intervention strategies to remove constraints on production conditions. Such interventions often target economic performance benchmarks such as milk per cow per day or costs per unit of milk produced. However, these are essentially partial measures of economic efficiency. The problem with these partial measures is that they concentrate on differences in average production between farms in the benchmark group, rather than on optimizing the farm-specific production in the benchmark group (Fraser and Cordina, 1999; Fraser and Hone, 2001; Stokes et al., 2007). Therefore, it would become necessary to use measures of efficiency which indicate performance indicator for the farming system as whole.

There are two strands of the literature on productive efficiency analysis: the parametric and stochastic frontier analysis (SFA) and the non-parametric data envelopment analysis (DEA). The SFA primarily relies on econometric regression to production function. This involves imposing ex ante specification of the functional form, focussing on the decomposition of the residual into a non-negative inefficiency element and the error term. On the contrary, the DEA approach utilizes a nonparametric approach to obtaining the production frontier. This does not involve imposing any assumption regarding a particular functional form but relies on the general regularity properties such as monotonicity, convexity, and homogeneity. This means that the main differences between the two approaches lie in specifications of relationships between sets of inputs and outputs in the process of production.

Each of the two approaches to productive efficiency analysis has its own strengths and weaknesses. While the virtues of the DEA lie in its general nonparametric frontier, it limitations are related to the fact that it attributes all deviations from the frontier to inefficiency by ignoring stochastic noises in the data. On the other hand, the strengths of the SFA lie in the stochastic, probabilistic treatment of inefficiency and noise but it can be implemented only by imposing a specific functional form and hence the efficiency indicators obtained can be sensitive to the chosen functional form. A number of studies have applied both SFA and DEA approaches to the same data but found no significant differences between the results (Resti, 1996; Coelli and Perelman, 1999; Johansson, 2005;Theodoridis and Psychoudakis, 2008).

The purpose of this paper is to derive and explain technical efficiency of smallholder dairy farms in selected districts in three East African Countries – Kenya, Rwanda and Uganda. The study benefited from a baseline survey conducted for the East African Dairy Development project – a large project launched during the first quarter of 2008 and being implemented in selected districts of the three countries with an overall objective of improving the livelihoods of smallholder households by doubling their income from dairy enterprise at the tenth year of the project time scale (Baltenweck, et al., 2009). In this study, a two stage approach was followed to conduct productive efficiency analysis: a mathematical programming to obtain relative positions of each dairy farm in terms of their level of economic efficiency and an econometric estimation to explain variations in the economic efficiency of the farms. The DEA approach was chosen to obtain the efficiency indicators primarily because it does not require imposing any specific form of the production function. This was applied and efficiency scores were obtained for a subset of farms that provided complete data on various input and output for their dairy enterprises.

The remaining part of this paper is divided into three sections. Section 2 discusses concepts and methods while section 3 highlights the study context. Section 4 presents details of results on economic efficiency scores and their determinants. Concluding remarks are made in section 5.

2 CONCEPTS AND METHODS

This section is intended to discuss conceptual and methodological issues in productive DEA. We highlight types and components of DEA efficiency measures and discuss specifications of the mathematical and econometric models.

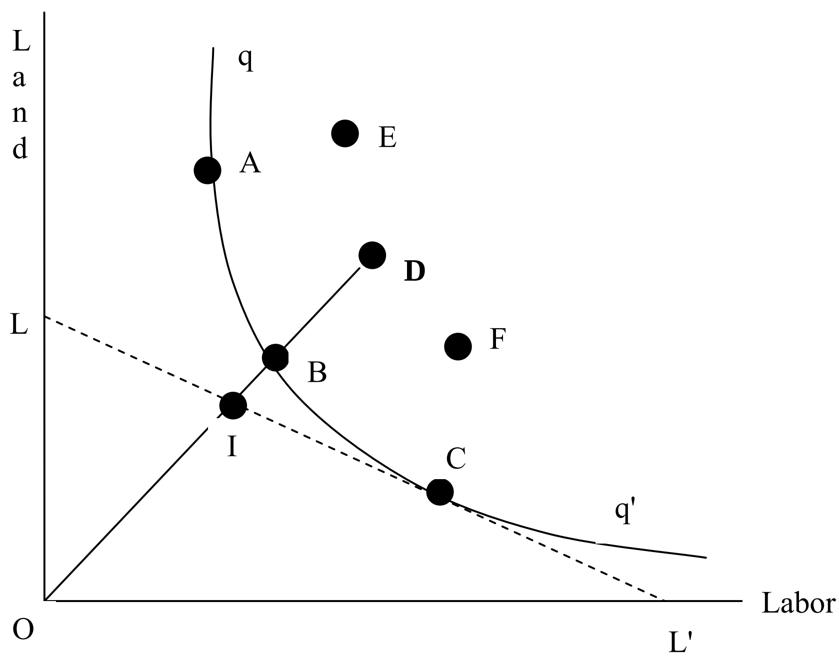
2.1 Concepts

Figure 1 **Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**provides a diagrammatic exposition using a simple example with six dairy farms, decision-making units or DMUs A, B, C, D, E, and F. Each DMU uses two inputs, land and labour to produce a litre of milk. DMUs A, B, and C are efficient dairy farms because they used the least amount of land or labour to produce a litre of milk, although each combined these inputs differently. The curve qq' is drawn by connecting A, B, and C (fully efficient farms) and hence it is referred to as "the efficiency frontier" in the DEA literature. The efficiency frontier represents the least cost combinations of scarce resource used to produce a given quantity of output.

The remaining three DMU (i.e., D, E, and F) are inefficient dairy farms because each use more of both land and labour compared to the efficient farms. Each of the inefficient farms could reduce it use of land or labour or both to produce a litre of milk. This would result in reaching on or closer to the efficiency frontier. For instance, if DMU F reduced uses of both land labour, then it would move to a point on the efficiency frontier reach somewhere between B and C.

For each DMU, an estimate of relative efficiency can be obtained by projecting a ray from the origin to the corresponding point. For farm D, the efficiency score, Θ, is given the ratio of the distance from the origin to the frontier curve, 0B, and the distance from the origin to D, or 0D. In other words, Θ = 0B/0D. It should be noted that for fully efficient DMU Θ = 1, but for all inefficient DMU, Θ < 1. The difference between 1 and Θ (or 1- Θ) indicates the proportion by which the DMU should reduce the use of both inputs to efficiently produce a litre of milk. For instance, if the efficiency score for D is 0.80, then it means it should reduce the use of land and labour by 20% (or to 80% of the current level) to achieve efficient level of production.

Figure 1: Efficiency analysis



A measure of efficiency discussed so far and represented by Θ represents technical efficiency (TE), maximal output from a given amount of inputs. However, TE does not take into account relative costs of inputs. Given prices of both inputs (wage rates and land rents), then it is possible to draw input cost ratios, represented by line LL'. DMU C is situated at the point of tangency between the input prices ratio line and the frontier curve (or the isoquant). This means that C fulfils conditions of TE as well as allocative efficiency (AE). The latter refers to optimal proportions in input use given their prices. DMU A and B are technically fully efficient but they are allocatively inefficient because they would need to combine use of land and labour differently by using less land and more labour.

The AE score is given by the ratio of the distance from the origin to the input price ratio line to the distance between the origin and the frontier curve. If we continue using as an examplie the ray from the origin in figure 1, then AE =0I/0B. Economic efficiency (EE), an indicator of total efficiency which combines the other two components of efficiency, is the product of TE and AE. In other words, EE = TE*AE= (0B/OD)*(0I/OB) =0I/0D.

2.2 Methods

Efficiency indicators are either input-oriented or output-oriented. Input-oriented efficiency measures indicate proportionate reductions in quantities of inputs without any reduction in the output quantity produced. On the other hand, output-oriented efficiency measures indicate the extent to which output quantity can be increased without any change in the quantities of inputs used. The relative size of the economic efficiency scores remains the same regardless of whether input-oriented or output-oriented method is applied.

We begin specification of the model by assuming that each DMU *j* has multiple inputs, $x_{i,j}$, and multiple outputs, $y_{k,j}$. A relative efficiency measure is defined by:

$$Efficiency_j = \frac{\sum_k u_k y_{k,j}}{\sum_i v_i x_{i,j}} \qquad 1$$

u and v are output and input weights, respectively. The weights constitute an essential element in determining relative efficiency of each DMU. It would be arbitrary to exogenously fix and assign uniform weights for all DMU. Each DMU *jo* is allowed to set its own weights in solving an optimisation problem to maximise its efficiency subject to the condition that all efficiencies of other DMUs remain less than or equal to 1 and the values of the weights are greater than or equal to 0:

$$\begin{aligned} Maximize\ \theta_0 &= \frac{\sum_k u_k y_{k,j0}}{\sum_i v_i x_{i,j0}} \\ st\ \frac{\sum_k u_k y_{k,j}}{\sum_i v_i x_{i,j}} &\leq 1 \\ u_k, v_i &\geq 0 \end{aligned} \qquad 2$$

The above system of equations can be transformed into a linear programming problem by imposing a further condition that the denominator should add up to unity. Hence, we would have the following LP formulation:

$$\begin{aligned} &Maximize\ \textstyle\sum_k u_k y_{k,j0} \\ &st\ \textstyle\sum_i v_i x_{i,j0} = 1 \\ &\textstyle\sum_i u_k y_{k,j} \leq \sum_i v_i x_{i,j} \quad \forall_j \\ &u_k, v_i \geq 0 \end{aligned} \qquad 3$$

In the DEA literature, there are two basic models widely applied in empirical research. These are the CCR model and the BCC model. The CCR model was pioneered by Charness, Cooper and Rhodes (1978). This model captures most essential feature of DEA efficiency scores discussed in the previous section and formalised equation 3. The CCR model is often implemented in a dual form and its output oriented specification is specified as:

$$Maximize\ z = \theta_{j0} \qquad 4$$

$$st\ \textstyle\sum_j \lambda_j y_{k,j} \geq y_{k,j0} \qquad 5$$

$$\theta_{j0} x_{i,j0} \geq \textstyle\sum_j \lambda_j x_{i,j} \qquad 6$$

$$\lambda_j \geq 0 \qquad 7$$

The CCR model (represented by equations 4-7) assumes constant returns to scale (CRS), which is only appropriate when all DMU's are operating at an optimal scale, i.e., one corresponding to the flat portion of the long-run average cost curve (Coelli 1996, p.17). The CRS assumption implies that all observed production combinations can be scaled up or down proportionally.

The BCC model (pioneered by Banker, Charnes and Cooper, 1984) extends the CRS formulation to account for variable returns to scale (VRS) which represents a piecewise linear convex frontier. The convexity condition is fulfilled by imposing an additional constraint that the weights denoted by λ_j should add up to unity

$$\sum_j \lambda_j = 1 \qquad \mathbf{8}$$

Thus, the BCC model is defined by equations 4-8. In the context of this study, imperfect competition and various constraints are likely to cause the dairy farms to operate at suboptimal scale. Accordingly, the BCC model based VRS assumption is adopted.

3 STUDY CONTEXT

This study used data from a household survey undertaken in various locations throughout three East African Countries – Kenya, Rwanda and Uganda (see Appendix 1). The survey was conducted as a baseline study for the East African Dairy Development (EADD) project, which was started in January 2008. EADD is a large development project whose overall goal was to transform the lives of 179 thousand families - approximately one million people - by doubling household dairy income at the end of the project timescale (ten years) through integrated interventions along the diary value chain – feeding, breeding, production, ancillary services, market access and knowledge applications.

While the EADD baseline survey consisted of three interrelated – household survey, survey of businesses related to dairy, and a participatory rural appraisal (PRA). This study used data from the household survey and the subsequent subsections will focus on briefly explaining method and approaches employed in implementing the household survey. Further methodological details on the household and the other surveys published in EADD project report (Baltenweck, et al., 2009).

3.1 Survey locations

The survey was conducted in selected target and control districts in two rounds. The first round was implemented during the second and third quarters of 2008 – five target and one control districts in Uganda (July, August), three target and one control districts in Rwanda (September, October), and three target and one control districts in Kenya (November, December). The second round covered districts where project activity started during the second year of the project timescale. Accordingly the surveys were conducted in two target and one control districts in Kenya during the months of July-September in 2009. In total, the baseline survey covered 17 districts, which represent diverse agro-ecological regions.

It should be noted that the surveyed districts were subsets of 42 target districts – 17 in Kenya, 15 in Uganda and 10 in Rwanda. Since the survey was primarily conducted to lay grounds for mid-term evaluation and final impact assessments, it was essential to systematically select the survey districts so that they would represent all project intervention locations. In addition to the integrated project interventions, for instance, performances of the dairy farms could also be affected by agro-ecological and socio-economic environments. In order to improve the representativeness of the survey sites, the following three steps were followed. First, by making use of IFPRI's "recommendation domains"[2], all survey districts were classified into the following four categories according to their agro-ecological and socio-economic profiles: (a) low market access/ low climatic potential, (b) low market access/ high climatic potential, (c) high market access/ low climatic potential, and (d) high market access/ high climatic potential. Second, the survey sites were then systematically selected ensuring that each category of the district was represented in the districts to be surveyed. Third, identification of suitable control sites posed a challenge. It was not practical to have a control site for each domain of the target sites surveyed. In the circumstances, a pragmatic approach was to select "control" sites which have average climatic potential and market access (the tow criteria defining the domains). Additionally, in order to minimize any potential interregional spill-over effects of the project

[2] The process involves characterizing wide project areas using two indicators of, climatic characteristic (LGP or Length of Growing Period) and access to urban centre (as an indicator of market access) using GIS layers. Using the median as the threshold for each indicator, the area is divided into the following domains: low market access / low climatic potential, low market access / high climatic potential, high market access / low climatic potential and high market access / high climatic potential

benefits, it was necessary to ensure that control sites would be as far away as possible from the project intervention districts: a range of 30 to 50 km was used.

3.2 Sampling approaches

The survey was conducted by interviewing only a relatively small percentage of the farmers in the community within each survey district. In order to ensure that the collected data represent properly the situation of the entire farmers' community, a sample size determined by applying the following power formula: $Y = \left(1.96\frac{SD}{ME}\right)^2$

Where Y is the minimum sample size; SD is standard deviation; ME is margins of error; and 1.96 is the 95% confidence interval. According to a previous study in the context of a small holder dairy development, standard deviation of milk production per cow was 4.3 (Staal et al 2001). This value was substituted in the above formula together with a marginal error of unity, i.e., ability to identify a one litre increase in milk production as being significant at the 5%. Accordingly, a minimum sample size was calculated as 71 households per district but this was increased to 75 to simplify enumeration in the field and allow for incomplete data. This means to total sample size was 1250 households (Kenya 525, Uganda 450, and Rwanda 300).

In all survey districts there was no sampling frame, a list of the population from which the required number of farmers would be selected using a particular sampling methodology. In the circumstances, a geographical random sampling proved to be most suitable (Vanden Eng, Jodi L, et al. 2007). First, each survey site was defined as the catchment area with the location of a dairy chilling plant at the centre (see Appendix 2). The corresponding radius in each country was chosen based on the maximum feasible distance farmers or traders would travel to supply milk to chilling plants. After consulting with project management and using expert opinion, the appropriate radius were determined as follows: 20km for Kenya and Uganda and 10km for Rwanda. The corresponding radius in each country was chosen based on the maximum feasible distance farmers or traders would travel to supply milk to the chilling plants; after consulting with project management and using expert opinion. Second, circular survey area was divided into grids cells which, depending on population density, ranged from 85 square meters (in Kandara district in Kenya) to 265 square meters (Bbaale district in Uganda). In all cases, urban, un-populated areas, forest and marshy areas were masked out. Finally, by applying a simple random sampling technique, 75 grids were selected from all the grids by assuming the area of each grid equates approximately to an average of homestead area of one farm household.

The process of identifying respondent households and approaching the interviewees for the survey involved the following procedure. Each of the 75 grids was assigned a latitude-longitude coordinate which were then uploaded into a global positioning system (GPS) instrument (see Appendix 3). The survey team was guided by a GPS instrument, goes to the location and conduct the questionnaire with a household situated nearest to the grid in that particular grid. If the survey team encountered more than one household household in the grid cell and the coordinate located in between then the team would randomly select one of the households. If there are no households in the vicinity of the GPS coordinate, then the survey team would randomly select a direction (north, south, east or west) and walk being guided by the GPS/compass to guide until a farmhouse.

3.3 The Questionnaire

A structured questionnaire was administered to each household identified and volunteered for interview. The survey begins by recording information on survey sites (country, district, sites, GPS coordinates of the household location where the interview has taken place); details of the respondent (such as position in the household). The questionnaire captured a good deal of information on different factors and activities relevant to dairy farming: household composition/ labour availability, farm activities and facilities , livestock inventory, milk production and marketing, livestock management, livestock health services, feeds and feeding, breeding, and household welfare.

The geographic random sampling meant not all of the 1250 households interviewed were cattle keepers. Cattle keepers were 67% of the total respondents or 837 farming households. The remaining respondents were farmers engaged in cropping and other agricultural activities. The number of cattle keepers who responded consistently to most variables of interest to this study was 704. This study is based on a sub-sample of these cattle keepers – 371 farming households who get at least 50% of their annual income from dairy farming. The rationale for such sub-sampling lies in the need to reduce degree of heterogeneity among the DMU in the DEA model.

4 DEA RESULTS

The statistical analysis in this study followed a two-stage approach to dairy farm efficiency analysis. First, the sizes of efficiency scores each of the 371 dairy farms were computed using the DEA approach. The difference in the distribution of the efficiency scores between farms and countries are then described. In the second stage, we undertake econometric analysis to explain the differences in the efficiency scores of each farm by a range of explanatory variables we obtain from the household survey data.

4.1 Inputs and outputs

The survey data provided multiple inputs and outputs for each of the 371 dairy farms. These were grouped into four output and nine input categories (see Table 1 below). Dairy related outputs include revenues from milk sales, imputed income of milk consumed on farm, income from sales of animals, and income from sale of manure. Some inputs are purchased (e.g. hired labour, concentrates, etc) while other input categories represent imputed costs of production (e.g., family labour, cattle housing, etc).

Table 1: Summary statistics of the variables in the study

Descriptions	*Mean*	*Median*	*Max*	*SD*
Outputs:				
Milk sales	516.6	287.0	7200.4	828.8
Milk consumed values	397.1	233.7	5775.3	569.8
Animal sale values	374.3	104.3	8757.1	969.4
Manure sales	0.2	0.0	26.1	1.7
Inputs:				
Cattle housing cost	16.6	0.0	2272.7	136.6
Hired labor	124.4	0.0	5114.4	446.9
Family labor	312.7	257.0	1778.3	237.5
Fodder cost	14.0	0.0	1944.5	112.4
Concentrate cost	64.4	0.0	3927.3	252.6
Water cost	12.2	0.0	951.4	70.2
Animal heath cost	133.3	76.9	2090.4	214.2
Extension services cost	7.3	0.0	678.0	40.9
Breeding cost	13.4	0.0	727.3	54.7

The summary statistics presented in Table 1 shows large variations among the farms in the level of different categories of outputs and input uses. As we expect, the largest proportion of income comes from milk sales but income from cattle sale and imputed value of milk consumed on farm also constitute reasonably high proportions of average dairy income. It should be noted that there are considerably large differences between the mean and median dairy incomes. From input side, imputed cost of family labour, hired labour and animal health costs are the three most important components in the total cost of production. Like outputs, there are high degree of variations between the means and median average figures.

4.2 Efficiency scores

The linear program problem formulated as a BCC basic model (as defined by equation 4') was implemented in the General Algebraic Modeling System (GAMS) programming language and the DEA efficiency scores were obtained (in formulating the GAMS version of the model, we followed Kalvelagen,2004).

Table 2: Distribution of farms by sizes of their technical efficiency scores

	<0.25	0.25-0.50	0.50-0.75	0.75-0.90	0.90-0.99	1
Uganda	**44**	**18**	**18**	**7**	**2**	**13**
Bbaale	11	3	5	0	1	2
Luwero	5	4	2	1	0	0
Masaka	2	3	2	2	0	3
Kakooge	17	4	6	1	0	7
Mukono	7	3	3	1	1	0
Bumanya	2	1	0	2	0	1
Rwanda	**18**	**15**	**12**	**6**	**2**	**12**
Bwisanga	2	1	1	1	0	3
Kabarore	6	2	3	1	1	4
Mbare	9	11	8	4	1	5
Nyagihanga	1	1	0	0	0	0
Kenya	**57**	**60**	**38**	**5**	**3**	**41**
Kabiyet	14	13	5	0	1	6
Metkei	17	20	3	0	0	2
Siongiro	12	9	10	0	0	2
Siaya	6	1	2	1	0	7
Soy	3	6	3	1	1	3
Kandara	2	6	7	1	1	14
Kaptumo	3	5	8	2	0	7
Total	**119**	**93**	**68**	**18**	**7**	**66**

Table 2 shows the distribution of economic efficiency scores obtained for the 371 farms located in 17 districts in the three East African Countries. The efficiency scores were classified into ten intervals to show possible clustering of efficient or inefficient dairy farms across the districts. From the total of the sampled 371 farms, 204 are located in Kenya, 102 in Uganda and 65 in Rwanda. From farms sampled in each country, the fully efficient farms (whose efficiency scores equals 1) are 20% in Kenya, 18% in Rwanda and 13% in Uganda.

As noted earlier, a farm with an efficiency score of 0.25 would need to increase output by 75% to reach the efficiency frontier without any increase in the level of input used in the process of production. Table 2 shows that 119 of the 371 farms have efficiency scores less than or equal to 0.25, which means that about 32% of the farms would need to increase milk output by at least 75% to reach the production frontier already reached by other dairy farms in the region. In Uganda, this proportion is even higher, with 43% of the farms needing to increase dairy production by making best use of inputs already at their disposal. The corresponding proportion of farms in this group in Kenya and Rwanda are 28% in each case. Overall, close to a third of all farms in the sample will need to increase output by at least 50% to reach the production frontier holding the level of input at the current level. This shows that there is considerable degree of improvement. It should be noted that the efficiency scores reported here are derived from the BCC basic model which means that it does not include scale effects.

Table 3: Descriptive statistics of the technical efficiency scores in the farms

Scores	Mean	SD	Min	Median	Max
<0.25	0.149	0.064	0.002	0.151	0.250
0.25-0.50	0.362	0.069	0.252	0.355	0.498
0.50-0.75	0.622	0.074	0.502	0.619	0.750
0.75-0.90	0.826	0.053	0.755	0.832	0.895
0.90-0.99	0.941	0.034	0.904	0.935	0.999
1.00	1.000	0.000	1.000	1.000	1.000
Total	0.488	0.323	0.002	0.410	1.000

Table 3 below provides additional information on summary statistics of the efficiency scores, primarily to show the distribution of the scores within each interval reported in Table 1. For instance, the mean averages for those farms with efficiency scores less than 0.25 was 0.15.

5 ECONOMERIC ANALYSIS

5.1 Model specification

As noted earlier, the second stage involves a regression analysis to relate DEA efficiency scores to exogenous factors. The econometric analysis is required to seek explanation as to why the DEA efficiency scores vary so much between farms and locations. Ramalho et al., (2010) provide a useful summary of how misspecification of the second-stage regression model may generate misleading results. The bounded nature of DEA scores limits the application of standard regression models to DEA scores. It is important to note that the values of the efficiency scores lie between 0 and 1. Critically, however, the efficiency scores do not take a value of zero which means ϴ is strictly greater than 0 (ϴ > 0). However, since fully efficient farms do exist, ϴ can take a value of 1, which means that ϴ ≤ 1. Thus, the realistic range of the values of DEA efficiency scores would be 0< ϴ ≤ 1. The unique combinations o f weak and strong inequalities bounding the range of values for DEA scores would have an important implication for the choice of econometric models.

In the DEA literature, a range of standard regressions are employed to explain DEA scores. These include ordinary, generalised, or truncated least squared regressions (Helfand and Levine 2004; Johansson 2005; Kolawole, 2009; O'Donnell and Coelli , 2003), ordered logistic regression (Usmay et al., 2009) and Tobit analysis (Alexander, 2003). However, as Ramalho et al. (2010, p. 2) observed, the standard linear models may not be appropriate because the predicted values may lie outside the unit interval and the implied constant marginal effects of the covariates on are not compatible with both the bounded nature of DEA scores and the existence of a mass point at unity in their distribution.

In this study we follow a fractional regression approach proposed by Papke and Wooldridge (1996) which pioneered direct models for the conditional mean of the fractional response that keep the predicted values in the unit interval through a more refined and flexible analyses using the generalized linear model (GLM). Papke and Wooldridge's (2007) provides further developments and applications of this method, a quasi-maximum likelihood estimation (QMLE) to obtain robust estimators of the conditional mean parameters with satisfactory efficiency properties. Moreover, a Stata code known as fractional logit," or "flogit" was developed and has simplified the implementation of the quasi-MLE with a logistic mean function.

5.2 Results

5.2.1 Descriptive analysis

Table 4below displays descriptive statistics for variables used in the econometric estimation. The explanatory variables can be classified into broad categories. The first category is related to household characteristics: age of household head, farming experience in years, education level, and family size. The mean and median age household head was 50 and 49 years respectively.

The average years of farming experience is 25 and average family size was about 5. The number of years of schooling is about 7.

Table 4: Descriptive statistics for the sample of dairy households

	Mean	SD	Min	Max	Median
Age of household head (years) (AGEHH)	50.2	15.1	18	100	49
Farming exp. of hh head (yrs) (FAEXHH)	24.7	15.8	1	75	21.5
Family size (adult equivalent) (FAMILY)	4.9	2.1	0.82	14.25	4.6
Edu. level of hh head (yrs) (EDUCATIONHH)	6.8	4.6	0	25	7
Farm size (acres) (FARM)	43.9	134.3	0.25	960	6
Number of cattle (TLU)[3]	15.9	26.7	0.7	277.2	7.85
Ratio of improved breeds (RATIO_IMBRDS)	0.5	0.5	0	1	0.6
Off-farm income (OFF-FARM)	Yes: 192 (1)			No: 179 (0)	
Member in a dairy coop. (DAIRYCOOP)	Yes: 53 (1)			No: 318 (0)	
Practice zero grazing (ZERO_GRAZING)	Yes: 37 (1)			No:334 (0)	
Conserve feed (FEED_CONSERVE)	Yes: 69 (1)			No: 302 (0)	
Grow fodder legumes (LEGUMES)	Yes: 20 (1)			No: 351 (0)	
Milk buyer dummies	Individual customers: 97; Private traders: 117; Dairy coop.: 45; Chilling plant: 29				
Country dummies	Uganda: 102; Rwanda: 65; Kenya: 204				
Recommendation domains[4]	HH: 155; HL: 81; LH: 33 LL:102				

The second group of explanatory variables are farm assets: farm size, number of cattle in tropical livestock units (TLUs), the proportion of improved breeds in the total number of livestock kept on the farm. The average farm size was 44 acres but there is a large variation among the farming households. The mean average TLUs owned by the households was about 16 but about 50% of the households actually keep less than 8. On average, half of the cattle kept on farm are improved breed. The econometric estimation also included a range of dummy variables which are expected to positively or negatively affect performances of the dairy farms. The latter group of variables are intended to capture a range of qualitative factors such as livestock management, technology adoption, marketing and agro-ecological conditions.

[3] TLU stands for Tropical Livestock Unit calculated by multiplying TLU factor and TLU breed factor. For example TLU factor for a cow is 1, while TLU breed factor for a Holstein-Friesian (pure) breed is 1.6. If a farmer has got 1 Holstein –Friesian pure cow, total TLU of that cow is 1*1.6=1.6

[4] EADD sites were selected based on 2 domains: Market access and Length of Growth Period (LGP), hence **HH** represents a site with High market access and High LGP, **LL**, site with Low market access and Low LGP, **HL,** High market access and Low LGP, **LH,** Low market access and High LGP.

5.2.2 Estimates

Starting with household characteristics, education level and farming experience of the head of the household has a positive effect on farm efficiency but household age and family size have negative effects. However, none of the variables in this group seem to have a statistically significant effect on dairy farm efficiency. Off-farm income has negative but insignificant effect.

From the three variables denoting farm assets in the model, the size of livestock (in TLUs) owned by the household does not only have a relatively large positive effect, but also its effect is highly significant at 1%. This could be associated with high levels of output (milk, cattle sales) derived from large cattle herds. It implies that 1% increase in number of cattle (in terms of TLU), increases the farm efficiency by 0.0033 units (0.3286/100). The results also agree with a study conducted in Wales England, where farms with a larger number of cows were found to be more efficient (Gerber and Franks, 2001). Similarly, the proportion of improved breeds in total livestock kept on farm also has a positive and statistically significant effect at 10% level. This could also explain the positive coefficient of the ratio of improved breeds in the herd, where a unit increase in one unit of improved breed increases the efficiency levels by 45%. However, although the size of farm owned by the household has a positive influence, this is not statistically significant.

Table 5 provides a summary of econometric results of the model. In order to ensure that the data is uniformly distributed, most level form variables were transformed to log form. These include age of household head, farming experience of the household head, family size, level of education of the household head, farm size; and number of cattle owned. Using log transforms enables modeling a wide range of meaningful, useful, non-linear relationships between dependent and independent variables (Shmueli, 2009). Using log-transform moves from unit-based interpretations to percentage-based interpretations (Vittinghoff, Glidden, Shiboski & McCulloch, 2004).

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Table 5: Results of the General linear model (GLM) with robust standard errors of factors influencing farm efficiency levels

Variable description	*Coefficient*	*Robust Standard Error*	*z*	*P>z*	*95% Conf. interval*
Log **(AGEHH)**	-0.1072	0.4310	-0.25	0.804	-0.9519288 - 0.737583
Log **(FAEXHH)**	0.0003	0.1733	0	0.999	-0.3394249 - 0.339926
Log **(FAMILY)**	-0.2671	0.2092	-1.28	0.202	-0.677216 - 0.142919
Log **(EDUCATIONHH)**	0.1948	0.1420	1.37	0.17	-0.0835866 - 0.473103
OFF-FARM	-0.0343	0.1779	-0.19	0.847	-0.3828521 - 0.314321
Log **(FARM)**	0.0372	0.0710	0.52	0.601	-0.1020264 - 0.176422
Log **(TLU)**	0.3286	0.1136	2.89	0.004***	0.1059005 - 0.551353
RATIO_IMBRDS	0.4463	0.2381	1.87	0.061*	-0.0203208 - 0.912886
LEGUMES	0.9892	0.3340	2.96	0.003***	0.3345673 - 1.643893
ZERO_GRAZING	1.0669	0.3347	3.19	0.001***	0.4108981 - 1.722895
FEED_CONSERVE	-0.1988	0.2191	-0.91	0.364	-0.6282585 - 0.23066
DAIRYCOOP	0.3163	0.2363	1.34	0.181	-0.1468431 - 0.779359
Individual customer milk buyer dummy	0.6379	0.2331	2.74	0.006***	0.1811201 - 1.094715
Private milk trader dummy	-0.0251	0.2274	-0.11	0.912	-0.4708374 - 0.420659
Chilling plant dummy	-0.0547	0.2585	-0.21	0.833	-0.5613117 - 0.451973
Uganda_dummy	-0.6112	0.3193	-1.91	0.056*	-1.237075 - 0.014682
Kenya_dummy	-0.2045	0.3556	-0.58	0.565	-0.9015913 - 0.492519
HH dummy	0.2591	0.3251	0.8	0.425	-0.3780425 - 0.896324
HL dummy	0.5766	0.3857	1.49	0.135*	-0.1793695 - 1.332573
LL dummy	-0.0505	0.3439	-0.15	0.883	-0.7244115 - 0.623501
Constant	-0.9004	1.3993	-0.64	0.52	-3.642934 - 1.842036
Deviance = 90.22799027 **Pearson = 75.05593911**				No. of obs = 227 Residual df = 206	
Variance function: V(u) = u*(1-u/1)		[Binomial]		Scale parameter = 1	
Link function : g(u) = ln(u/(1-u))		[Logit]		(1/df) Deviance = 0.438	
Log pseudolikelihood = -113.5536042		AIC = 1.185494		(1/df) Pearson = 0.3643492	
		BIC = -1027.312			

Note: *=Statistically significant at 10%; **=Statistically significant at 5%; *=Statistically significant at 1%**

The econometric results suggest growing fodder and and/or practice zero-grazing has a highly significant effect (both at 1%) on hat dairy farms efficiency. On the other hand, feed conservation seems to have a rather unexpected negative effect although this is not statistically significant. In terms of marketing outlets or buyer types, selling directly to consumers (e.g. neighbors, organizations, etc) has a strongly positive and statistically significant influence on dairy farm efficiency. The interpretation of the coefficient suggests that selling of milk to individual customers increases the efficiency levels by about 63%. . Contrary to our expectation, although not significant, sale of milk to a chilling plant was found to be negatively associated with efficiency scores. Membership of dairy cooperatives does have a positive effect but not significant statistically.

The coefficient of Uganda dummy in the model is significant and negative. This implies that, efficiency levels of farms located in Uganda are 60% less compared to the other countries. In terms of recommendation domain, it was expected that sites with high market access and high LGP would be more efficient. The HH (high market access/ high LGP) domain however was not significant but positive. The coefficient of the HL (high market access/ low LGP) was positive and significant. This suggests that, the location of a site in an area with high market access and low LGP is associated with 57% increase in efficiency level.

6 CONCLUSIONS

The study was set out to measure and explain economic efficiency of dairy farms sampled from seventeen districts in three East African Countries. A DEA methodology was used to measure out-put oriented efficiency scores, which were obtained allowing variable returns to scale. The latter condition is suitable to conditions of dairy farming in East Africa where various constraints inhibit dairy farms from realizing their potentials by expanding their scales of operation.

One of the main findings of this study is to establish the extent to which dairy farms in the region are operating at a considerably high level of inefficiency. On the one hand, from farms sampled in each country, the fully efficient farms (whose efficiency scores equals 1) are 20% in Kenya, 18% in Rwanda and 13% in Uganda. On the other hand, about 32% of the 371 farms studied would need to increase milk output by at least 75% to reach the production frontier already reached by other dairy farms in the region. In Uganda, this proportion is even higher, with 43% of the farms needing to increase dairy production by making best use of inputs already at their disposal. The corresponding proportion of farms in this group in Kenya and Rwanda are 28% in each case. Overall, close to a third of all farms in the sample will need to increase output by at least 50% to reach the production frontier holding the level of input at the current level.

We have gone further and examined determinant factors for dairy farm efficiency. Technology adoption factors such as existence of improved breeds in the herd and feed and fodder innovations (whether or not the farmer is growing legumes, etc) have positive and statistically significant effect on the levels of economic efficiency. Similarly, farms practicing zero grazing are characterized by high level of economic efficiency.

Some of the most surprising findings in this study are related to marketing factors. Contrary to what was expected, membership of dairy cooperatives or selling to chilling plants has negative but not statistically insignificant effect on dairy performance. Interestingly, selling directly to consumers or institutions seems to be more associated with improvements in economic performances of dairy farms. Further investigations into the latter intriguing results are left for subsequent research.

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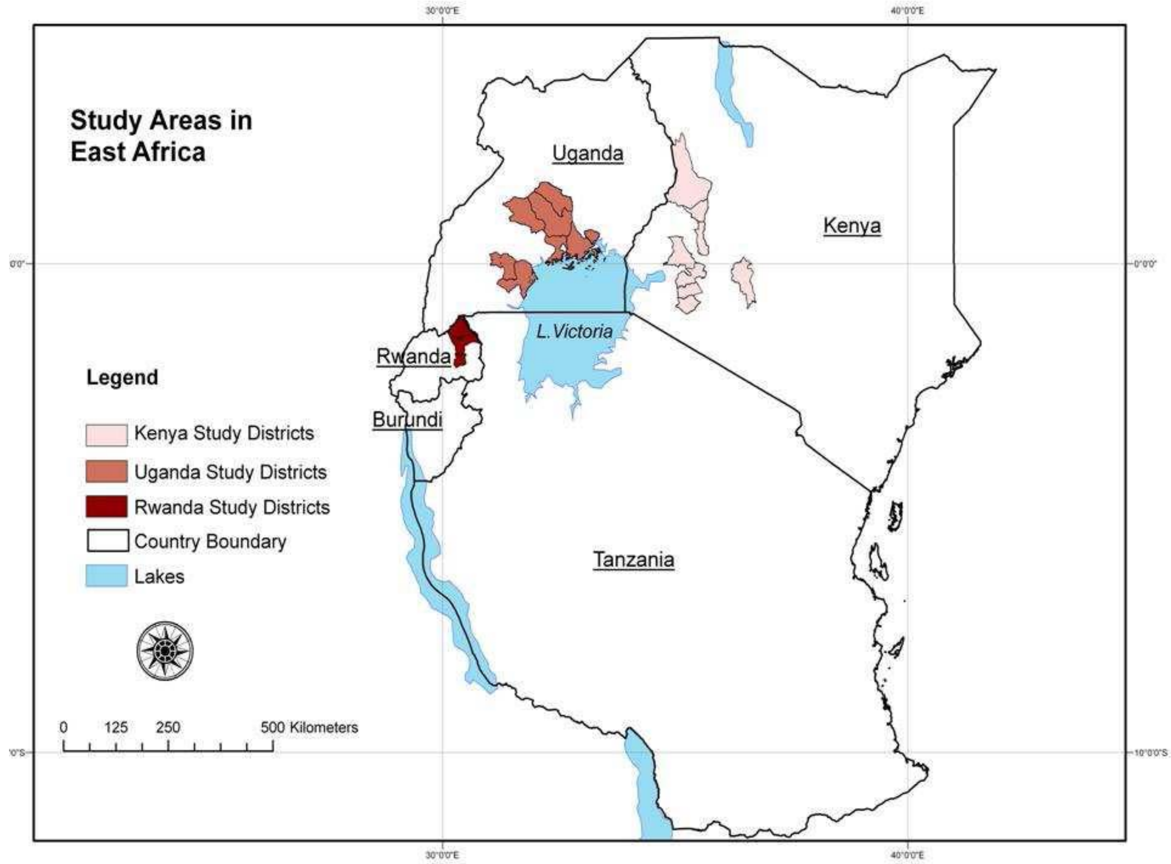
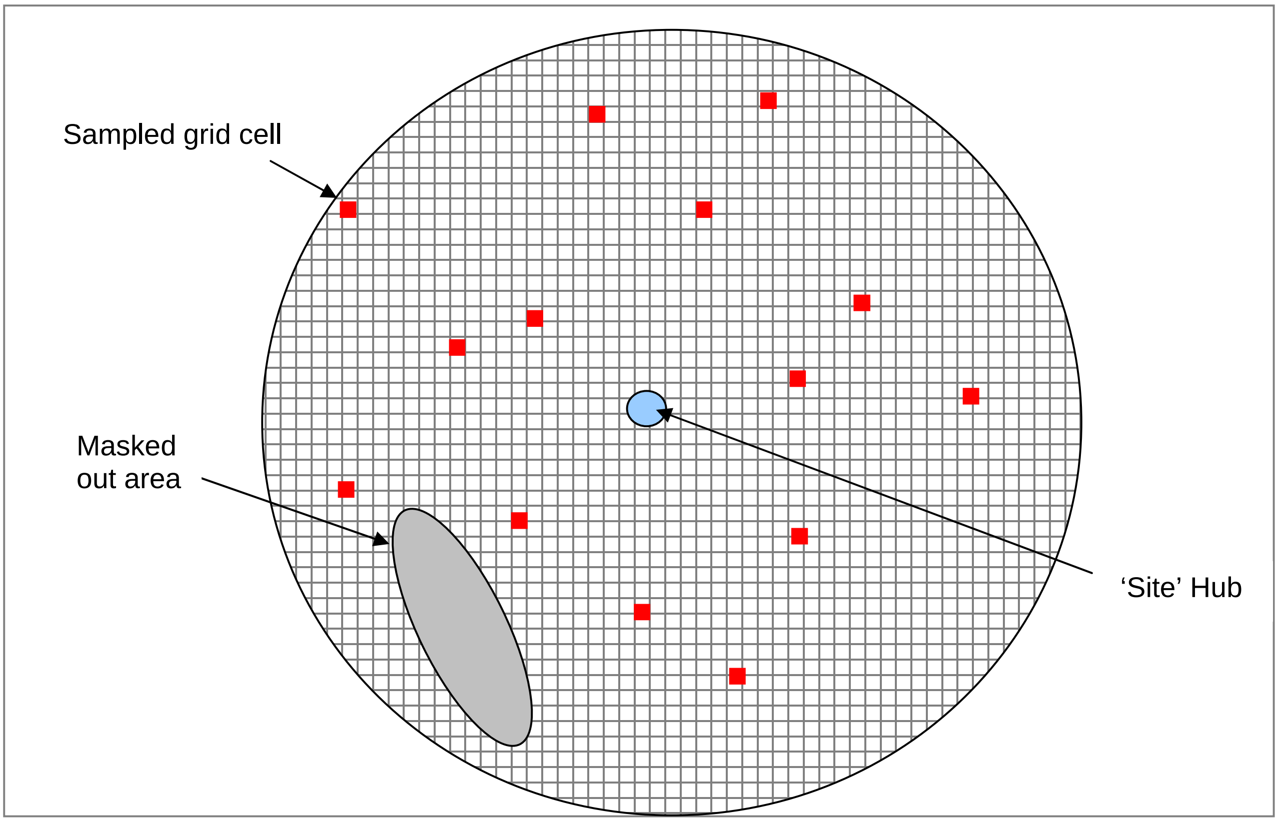
Appendix 1 - Project areas for East Africa Dairy Development Project


Study Areas in East Africa
Uganda
Kenya
L. Victoria
Rwanda
Burundi
Tanzania
Legend
Kenya Study Districts
Uganda Study Districts
Rwanda Study Districts
Country Boundary
Lakes
0 125 250 500 Kilometers

Appendix 2 – schematic representation of the geographic sampling frame



Appendix 3 - Rwanda - Bwisanga/Gasi (Rwamagana district)