Examining Returns to Scale in Smallholder Dairy Farms in East Africa

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Abstract

The study examined returns to scale in 371 dairy farms sampled from different districts in East Africa. First, data envelopment analysis (DEA) was applied to obtain three types of returns to scale – constant returns (CRS), variable returns (VRS) and increasing returns to scale (IRS). This revealed that 80 percent of the farms were scale inefficient. We find inverse relationship between scale efficiency and their size (measured in tropical livestock units), implying that the prevailing farm inefficiencies were not due to their small size but other farm resource constraints. Second, econometric analysis was conducted to explain differences among the farms across the three cases of returns to scale. Zero-grazing emerged as the most important determinant of farm efficiency. The scale efficiency based model fits the data better than the alternative CRS and VRS based econometric models.

Keywords: DEA, fractional regression, returns to scale, dairy, East Africa
JEL: 010, Q12, Q13, Q16

1 Introduction

Food security and poverty concerns in Sub-Saharan Africa have attracted the attentions of policy makers, researchers and donors alike. The livelihood of the majority of the population in this region is based on small household farms. For this reason, agricultural development programs in most countries often target introducing novel farming practices or improving productivity of the small farming units. This is often measured in terms of more output per unit of input. Policy interventions and development projects are designed to improve productivity indicators, such as crop harvests per hectare or milk yield per cow. However, these are essentially partial measures of efficiency since they represent average production of the target farms. It would prove useful to focus on optimizations of the farm-specific efficiency indicators for the benchmark groups of farms (FRASER and CORDINA, 1999; FRASER and HONE, 2001; STOKES et al., 2007).

There are different approaches in the literature with regard to types of farm specific efficiency indicators as well as methods applied to compute them. The focus has often been on measuring overall efficiency scores for the relationship between inputs and outputs at farm level and then seeking explanations for differences among the farming units (GERBER and FRANKS, 2001; JOHANSSON, 2005; AJIBEFUN, 2006; UZMAY et al., 2009; GEBREGZIABHER et al., 2012; GELAN and MURIITHI, 2012). However, it has become increasingly important to isolate and explain farm efficiencies related to economies of scale of operations (KERSTENS and EECKAUT, 1998; JAFORULLAH and WHITEMAN, 1999).

On methods of efficiency measurements, there are two strands in the literature. These are the parametric or stochastic frontier analysis (SFA) and the non-parametric data envelopment analysis (DEA). The SFA follows econometric methods and imposes specific functional forms to decompose the residual into a non-negative inefficiency element and the error term. The DEA approach relies on linear programming methodology, a nonparametric approach, to obtain the production frontier by imposing the general regularity properties such as monotonicity, convexity, and homogeneity (RESTI, 1997; COELLI and PERELMAN, 1999; JOHANSSON, 2005; THEODORIDIS and PSYCHOUDAKIS, 2008; COOPER et al., 2011).

The objective of this study is to examine returns to scale in smallholder dairy farms in selected districts in three East African Countries – Kenya, Rwanda and Uganda. The study builds on a previous paper by GELAN and MURIITHI (2012), which focussed on measuring and explaining overall technical efficiency. This study extends the analysis by decomposing the overall efficiency scores into different types of returns to scale efficiency indicators.

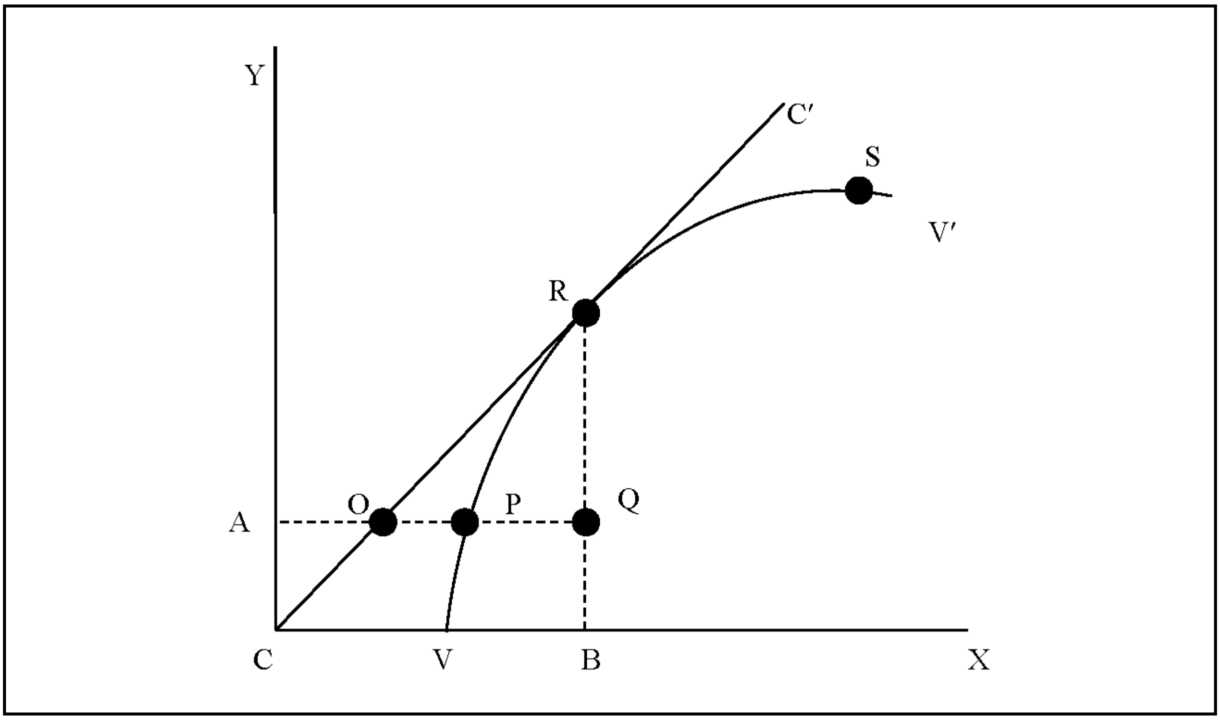
A two-stage approach was adopted: (a) a mathematical programming to obtain relative positions of each dairy farm in terms of their level of efficiencies; and (b) an econometric estimation to explain variations in returns to scale among the farms (GRAHAM and FRASER, 2003; KUMAR and GULATI, 2008; TUNG, 2013). The DEA approach was applied to compute the overall efficiency as well as different returns to scale indicators. Each category of the efficiency score was explained by applying econometric models with similar sets of explanatory variables. Finally, model fitness tests were conducted to select the most appropriate model. This indicated that scale efficiency based econometric model fits the data more than the alternative models. This means that overall technical efficiency measurements would not sufficiently reveal the nature of determinants of returns to scale.

The remaining part of this paper is divided into four sections. Section 2 discusses concepts and methods and section 3 highlights issues related to data sources and model specifications. Section 4 presents results of the DEA model that is distributions of the efficiency scores. Section 5 discusses results of the econometric models, providing explanations for differences in efficiency scores of the dairy farms, while Section 6 provides the concluding remarks.

2 Conceptual Framework

This section discusses conceptual issues related to types and components of DEA efficiency measures. The theoretical analysis in this section closely follows COELLI et al. (2008). Figure 1 illustrates various concepts of efficiency measures by using six dairy farms or decision-making units (DMUs) which are denoted by points O, P, Q, R, and S. Each farm uses a composite input, X, to produce a composite output, Y. The 45^{o} line, CC′, represents constant returns to scale (CRS). The slope of this line is a constant, i.e., a unit increase in the composite input leads to equal one unit increase in the level of output at all points along the line CC′. The fact that points O and R lie on the line CC′ indicate that these farms are fully efficient and they operate under conditions of CRS.

Figure 1. Efficiency analysis



Source: authors' illustration

On the other hand, the curve VV′ represents variable returns to scale (VRS) production function. Unlike the CRS case, a unit increase in the level of input use leads to variable quantities of increments in output under VRS (along the curve VV′). DMUs P, R, and S are fully efficient farms producing with, respectively, increasing returns to scale (IRS), CRS, and decreasing returns to scale (DRS).

Point Q denotes an inefficient farm by both the CRS and VRS criteria. The level of its technical inefficiency can be measured by using an input or output oriented DEA approaches. Input-oriented efficiency measures indicate proportionate reductions in quantities of inputs without any change 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 quantity of input used. The relative size of the technical efficiency scores remain the same regardless of whether input-oriented or output-oriented method is applied. For instance, using the CRS based input oriented technical inefficiency, ϴ, is given by the ratio of the line projected from the vertical axis (which denotes the level of output) to the CRS line, AO) and the same line extended to the inefficiency point (AQ). In other words, $\Theta = AO/AQ$. The output oriented technical efficiency score is obtained by projecting lines from the horizontal axis, i.e., $\Theta = BQ/BR$.

For the CRS case, the value of the technical efficiency score remains the same regardless of whether input or output oriented method is applied. This means $\Theta = AO/AQ = BQ/BR$. This means that either the level of output can be increased from O to R keeping the quantity of input at the same level, B, or, alternatively, the level of input can be reduced from B to a point below O to produce the same level of output, A. For the VRS, given that change in the level of input use causes variable changes in the level of output along the curve VV′, the output and input oriented methods yield different technical efficiency scores. It should be noted that for fully efficient DMU, $\Theta = 1$, but for all inefficient DMUs, $\Theta < 1$. The difference between 1 and ϴ (or $1- \Theta$) indicates the proportion by which the DMU can increase output without any change in the amount of input used. For the same level of output, we obtain different technical efficiency scores for the CRS and the VRS. For instance, for point Q, the output oriented technical efficiency scores for the CRS (TE_C) and VRS (TE_V) at output level A are given as $TE_C = AO/AQ$ and $TE_V = AP/AQ$.

The distance between the CRS line and the VRS curve (OP) is caused by differences in scale efficiency (SE). The latter is given by the ratio of the TE_C to TE_V, i.e. $SE = TE_C/TE_V = (AO/AQ)/(AP/AQ) = AO/AP$. It follows that the CRS technical inefficiency can be decomposed into ‘scale inefficiency’, OP, and ‘pure inefficiency’, PQ. If $SE = 1$, then the farm is scale-efficient; its combination inputs and outputs is efficient both under CRS and VRS (BIELIK and RAJČÁNIOVÁ, 2004). In other words, if the technical efficiency scores for the CRS and VRS are equal, it means the farm is operating at optimal scale. On the other hand, if SE < 1, then the farm is scale-inefficient or operating at a suboptimal scale. In other words, the farm is too small or too large.

The SE scores do not indicate whether or not the DMU is operating at the IRS or DRS ranges. This can be specified by solving for a DEA with non-increasing returns to scale (NIRS) (see Eq. 5′ in section 3 below). In the context of the diagram above, the NIRS case is given by a locus of points represented by CORSV′. The relevant returns to scale along the NIRS locus is obtained by the NIRS based scale efficiency scores (SE_I) as ratios of the CRS technical efficiency scores (TE_C) and the NIRS technical efficiency scores (TE_I), i.e., $SE_I = TE_C / TE_I$. If $SE_I = 1$, then the DMU is operating at IRS range of the VRS curve. However, if $SE_I < 1$, then the DMU is operating at DRS range. This means that, in the context of Figure 1, any point up to and including R is considered as an IRS range but any point beyond R, such as S, denote a DRS range.

3 Model Specification and Data

3.1 Model Specification

In the previous section, we have used a diagrammatic exposition to illustrate key concepts in the DEA literature. In this section, we turn our attention to mathematical relationships between the variables and specify the DEA model in terms of linear programing based optimisation problem.

We begin by assuming DMUs produce multiple outputs by using multiple inputs. If we denote DMU_j, the multiple inputs and outputs by $x_{i,j}$ and $y_{k,j}$ respectively, then relative technical efficiency measure is given by the ratio of the weighted sum of outputs to the weighted sum of inputs. In other words, the technical efficiency score of a DMU is calculated as weighted average output per unit of weighted average input. While comparing different DMUs, it is the weights assigned to inputs and outputs used by each DMU that will play a critical role. It would be arbitrary to exogenously fix and assign uniform weights for all DMU. The weights for each DMU*jo* is endogenously determined, they are allowed to vary in the process of solving for a DEA problem through optimisation using Linear Programming approach. This is done by maximising the efficiency score that particular DMU*jo* 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:

The specification of the LP problem in the DEA literature follows one of the two basic models widely applied. The first one was pioneered by CHARNES et al. (1978), and it is called the CCR model. This model captures most essential feature of DEA efficiency scores discussed in the previous section. The CCR model is often implemented in a dual form and its output oriented form is specified as:

$$\boldsymbol{Maximize\, z} = \Theta_{\boldsymbol{j0}} \tag{1}$$

$$\boldsymbol{st} \quad \sum_{\boldsymbol{j}} \boldsymbol{\lambda_j y_{k,j}} \geq \boldsymbol{y_{k,j0}} \tag{2}$$

$$\Theta_{\boldsymbol{j0}} \boldsymbol{x_{i,j0}} \geq \sum_{\boldsymbol{j}} \boldsymbol{\lambda_j x_{i,j}} \tag{3}$$

$$\boldsymbol{\lambda_j} \geq \boldsymbol{0} \tag{4}$$

where λ_j denote the input and output weights for DMU_{jo}. The CCR model (represented by equations 1-4) assumes constant returns to scale (CRS), which is only appropriate when all DMUs are operating at an optimal scale, i.e., one corresponding to the flat portion of the Long-run average cost curve (COELLI et al., 2008). The CRS assumption implies that all observed production combinations can be scaled up or down proportionally, (see the 45^o line in Figure 1 which denoted a CRS case, implying such proportionate changes in inputs and outputs).

The second DEA model is pioneered by BANKER et al. (1984) and hence often referred to as the BCC model. It extends the CRS formulation to account for variable returns to scale (VRS) which represents a piecewise linear convex frontier. The BCC model retains most of the specifications outlined in Equations (1)-(4) above but it extends the CRS formulation to account for the VRS conditions through a piecewise linear convex frontier. The convexity condition is imposed by an additional constraint that the weights should add up to unity:

$$\sum_{\boldsymbol{j}} \boldsymbol{\lambda_j} = \boldsymbol{1} \tag{5}$$

Thus, the CCR and the BCC models are defined by Equations 1-4 and Equations 1-5, respectively. As noted earlier, the VRS technical efficiency scores would not distinguish between cases where the DMU is operating with the increasing returns to scale or decreasing returns to scale. The NIRS specification distinguishes between areas of the IRS and DRS ranges of the VRS. In the context of a linear programming model, the NIRS case is specified by modifying equation (5) as:

$$\sum_{\boldsymbol{j}} \boldsymbol{\lambda_j} \leq \boldsymbol{1} \tag{5′}$$

The VRS technical efficiency scores are obtained by solving for the Equations 1-5, but the NIRS technical efficiency scores are obtained by solving for Equations 1-4, and Equation 5′.

3.2 Data

The DEA model was implemented by using survey data collected from 17 districts in three East African countries - Kenya (7 districts), Uganda (6 districts) and Rwanda (4 districts). BALTENWECK et al. (2009) provide detailed description of methodology and further details of this survey. For the discussion in this section, we heavily borrowed from GELAN and MURIITHI (2012). The survey was conducted in 2008 and 2009 and the primary purpose of the survey was to collect baseline data for the East African Dairy Development project (EADD). The baseline survey was designed with a view of facilitating the groundwork for mid-term and final project impact assessments. The surveyed districts were strategically selected ensuring they represent the diverse agro-ecological zones in the three countries.

In each survey district, about 75 households were randomly selected and interviewed through face-to-face interview technique. Field enumerators used a questionnaire to collect 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. Before the face-to-face household interviews were conducted, focus group discussions and key informant interviews were carried out. The focus group discussions involved farmers, while key informant interviews were conducted among managers of dairy processing plants and officials from the Ministry of Agriculture working in the study areas. The purpose of these prior discussions was to provide qualitative information regarding the dairy farms including types of dairy cattle kept in the area, feeds, breeding systems as well as expected levels of outputs. The qualitative information gathered from these discussions was provided to the enumerators during the questionnaire training as a background of the study areas, to ensure high level of precision of the data to be collected afterwards. The collected household data was further validated using a similar exercise with key informants and data collected previously in these areas for other studies.

A total of 1,275 households were interviewed but only 62% of the respondents were cattle keepers. 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. However, this study is based on a sub-sample of cattle keepers – 371 farming households who get at least 50% of their annual income from dairy related farming activities. These geographic distributions of these farms are given as follows: Kenya, 204; Rwanda, 65; and Uganda, 102. The rationale for such sub-sampling lies in the need to reduce degree of heterogeneity in types of farming activities among the DMU in the DEA model.

4 Descriptive Statistics on the DEA Scores

This section begins by presenting descriptive statistics on ranges of input and output variables applied to compute efficiency scores. This is followed by discussion on how various DEA scores were computed for the 371 dairy farms and results are discussed in this section. The discussion focus on difference in the distribution of the efficiency scores by countries and farm sizes (measured in number of cattle in tropical livestock units or TLUs).

4.1 Descriptive Statistics on Input and Output Variables

The multiple inputs and outputs for each of the dairy farms are presented in Table 1. These were grouped into four output and ten input categories. Dairy related outputs included revenues from milk sales, imputed income of milk consumed on farm, income from sales of animals, and income from sale of manure. For most outputs categories actual monetary incomes obtained from selling the products were utilised but milk consumed on farm was imputed income. Similarly, some input categories (hired labour, concentrates, etc.) are purchased but costs of other input categories (e.g., family labour, cattle housing, etc.) were imputed costs.

Table 1. Summary statistics of the variables in the study (in US$)

Descriptions	Mean	SD	Median	Max
Outputs				
Milk sales	516.6	828.8	287	7,200.4
Milk consumed values	397.1	569.8	233.7	5,775.3
Animal sale values	374.3	969.4	104.3	8,757.1
Manure sales	0.2	1.7	0	26.1
Inputs				
Cattle housing cost	16.6	136.6	0	2,272.7
Hired labor	124.4	446.9	0	5,114.4
Family labor	312.7	237.5	257	1,778.3
Fodder cost	14	112.4	0	1,944.5
Concentrate cost	64.4	252.6	0	3,927.3
Water cost	12.2	70.2	0	951.4
Animal heath cost	133.3	214.2	76.9	2,090.4
Extension services cost	7.3	40.9	0	678
Breeding cost	13.4	54.7	0	727.3

Source: authors' calculation using survey data

There are large variations among the farms in the values of different categories of outputs and input uses. Given the criterion used to select the 371 sub-sample of farms, milk sales constitutes the largest proportion of farm revenues as expected. Income from cattle sale and imputed value of milk consumed on farm also constitute reasonably high proportions of average dairy income. There are large divergences between the mean and median indicators of most input and output variables. These can be attributed to farm characteristics such as size and location.

4.2 Size and Distributions of the DEA Efficiency Scores

Linear program problems were formulated for the basic CCR and BCC models (as defined by Equations 1-5′) and were solved using the General Algebraic Modeling System (GAMS) programming language. The DEA efficiency scores were obtained by adapting KALVELAGEN (2002) to the context of this study. Three separate models were formulated: the CCR for the CRS (Equations 1-4); the BCC model for the VRS (Equations 1-3, and 5) and the BCC model specifically for the NIRS (Equations1-3 and 5′).

Table 2 shows the distribution of economic efficiency scores obtained for the 371 farms. The efficiency scores were grouped into five intervals of efficiency scores. Starting with fully efficient farms, only about 12% (or 45) of the farms were located on the production possibilities frontier. This means that overall technical efficiency scores of about 88% farms is less than unity. Efficiency scores of 43% of the farms was less than 0.24, which means that these farms can increase output by 68% without any increase in the level of farm inputs. The mean and median overall efficiency scores were 0.39 and 0.29, respectively. Overall inefficiency can be attributed to “pure technical efficiency” scores refer to the case of the VRS or scale efficiency.

About 18% (or 67) farms are fully efficient according to the VRS or BCC scores. This indicates that 82% of the farms can gain some degree of efficiency by improving their farm administrative and management methods in terms of the way they combine inputs and outputs in efficient manner. The mean and median VRS efficiency scores were 0.49 and 0.41, respectively. For 20% (or 74) of the farms their CCR and BCC scores are equal which means that are they are scale efficient (note that scale efficiency scores are calculated as the ratio of CCR to BCC scores). The remaining 80% of the farms would need to adjust their scales of operation as well as farm management skills in order to move to the production possibilities frontier.

Table 2. Frequency distribution of efficiency scores

Efficiency score intervals	Overall Technical Efficiency (TE_C)		Variable Returns to Scale (TE_V)		Scale efficiency (SE)	
	Freq.	%	Freq.	%	Freq.	%
Total	**371**	**100**	**371**	**100**	**371**	**100**
0.00 - 0.24	160	43	114	31	4	1
0.25 - 0.49	103	28	96	26	51	14
0.50 - 0.75	44	12	70	19	98	26
0.75 - 0.99	19	5	24	6	144	39
1.00	45	12	67	18	74	20
Average scores:						
Mean	0.39		0.49		0.78	
Median	0.29		0.41		0.84	
Returns to scales (no of farms):						
CRS	101					
IRS	263					
DRS	7					

Source: authors' calculation using survey data

It should be noted the relative sizes of the average (mean and median efficiency) scores with CCR scores being larger than VRS efficiency scores which in turn are larger than scale efficiency scores (TUNG, 2013; LEE, 2009; KUMAR and GULATI, 2008). The pure technical efficiency or VRS scores do not distinguish between types of returns of scales. The distinctions can be established by applying the following criteria:

i) If TEc = TEv, then CRS

ii) If TEc < TEv and SE = NIRS, then DRS

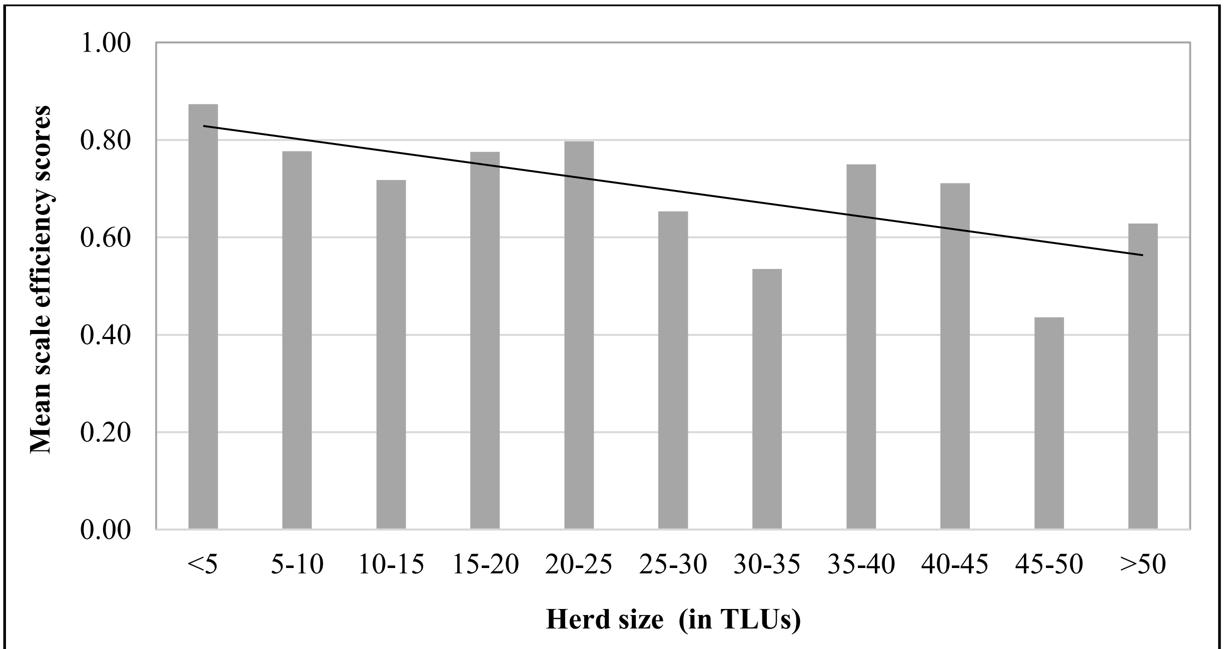
iii) If TEc < TEv and SE ≠ NIRS, then IRS

The last three rows of Table 2 display farms classified into the three returns to scale categories. About 27% (or 101) farms are characterized by CRS which means that they can change scale of operation only by proportionately increasing or decreasing input-output combinations. On the other hand, the majority of the farms (71%) are characterized by IRS. This implies that the DMU can gain efficiency by increasing production and become scale efficient. On the other hand, a small number of units (7 farms) were found to be operating in the DRS range, which means they would need to reduce scale of operation to gain efficiency improvements.

It should be noted that the farms sampled for this study were dependent on livestock keeping and their livelihood is dependent on dairy and related products. In this context, it is important to explain why most farms were characterized by IRS, suggesting the farms can increase their efficiency by increasing their scale of operation. Does this mean increasing the number of animals?

In order to seek answer for this question, we examine the relationships between farm scale efficiency and herd size measured by number of animals on farm in Tropical Livestock Units (TLUs). This is displayed in Figure 2 where the vertical axis denotes scale efficiency scores while the horizontal axis presents animal numbers (in TLUs) in eleven size bands. The bar graphs and the trend lines clearly display the existence of inverse relationships between farm efficiency and her sizes. For instance, the smallest size band of less than 5 TLUs have an average efficiency score of 0.87 SE score but the last two herd size bands (of 45-50 and >50 TLUs) have average efficiency score of 0.53 SE scores. This indicates that the former group is about 34% more efficient compared to the latter group.

Figure 2. Relationships between herd size and efficiency scores



Source: authors' calculation using survey data

This study finds inverse relationships between herd size and efficiency in agriculture as reported in many other studies (VAN ZYL et al., 1995; ADESINA and DJATO, 1996; JAVED et al., 2011). However, using the Polish case study LATRUFFE et al. (2005) observed direct relationships betweenherd size and farm efficiency scores.

It follows from the above discussion that the majority of the farms are likely to become efficient by focussing on improving other farm management options rather than increasing herd sizes. The likely reason for small farms to be much more efficient compared to other farms with larger herd sizes may lie in the possibility of providing fewer animals with better quantities and qualities of feed as well as looking after the health of their animals. However, larger herd size is not necessarily the source of inefficiency but the difficulty of providing larger herds with reasonably good amount of feed that is likely to make larger units less efficient.

5 Econometric Analysis

5.1 Model Specification

The second stage involves a regression analysis by relating DEA efficiency scores to a range of explanatory variables. The essence of conducting the econometric analysis lies in seeking explanation for variations of efficiency scores between farms. RAMALHO et al. (2010) provide a useful summary of how misspecification of the second-stage regression model may generate misleading results. It is important to bear in mind that the values of the efficiency scores lie in the range strictly greater than 0 (> 0) but loosely less than 1 (≤ 1). The reason is that fully efficient farms do exist and hence Θ can take a value of 1, which means that $\Theta \leq 1$, but there is no farm whose efficiency can realistically be reduced to 0. In other words, any existing farm should have some degree of positive efficiency, however low it can get. Consequently, all DEA scores lie in this range: $0 < \Theta \leq 1$. The unique combination of weak and strong inequalities bounding the range of values for DEA scores has important implications for the choice of econometric models.

The second stage in the farm efficiency analysis have often replied on a range of standard regression, including ordinary, generalised, or truncated least square regressions (HELFAND and LEVINE, 2004; JOHANSSON, 2005; O'DONNELL and COELLI, 2005; OGUNDARI, 2009), ordered logistic regression (FULLERTON, 2009; UZMAY et al., 2009) and Tobit analysis (ALEXANDER et al., 2003). However, applications of standard regressions have increasingly been criticized in recent years. For instance, RAMALHO et al. (2010: 2) stated that 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 are not compatible with both the bounded nature of DEA scores and the existence of a mass point at unity in their distribution.

We follow a fractional regression approach proposed by PAPKE and WOOLDRIDGE (1996). The latter pioneered development of a model 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 (2008) 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, the development of 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 Descriptive Statistics

Table 3 below displays descriptive statistics for variables used in the econometric estimation. The first three rows provide statistics for the dependent variables, which are indicators of returns to scale, measured in terms of CRS, VRS, and SE scores. The remaining rows in the table relate to different categories of social and economic factors, which explain or determine the efficiency of dairy farms. In addition to the averages (mean and median), the range and standard deviations of the dependent and explanatory variables are presented.

The explanatory variables are classified into several groups and selected based on literature review and theoretical information on the subject matter. Correlation matrices analysis was also conducted to eliminate highly correlated variables. The first category is related to household characteristics: age of household head, farming experience in years, education level, and family size. Household characteristics could influence farm management skills,whether the farmers are able to combine inputs and outputs in an efficient manner (TAUER and STEFANIDES, 1998). For instance, better educated household heads may have superior business management skills that are likely to enhance efficient use of inputs and generation of efficient level of net income (STOKES et al., 2007). UZMAY et al. (2009) find family size and farming experience to be positively related to technical efficiency of dairy farms. A large household size is often interpreted as a source of labour, which is important for intensive farm enterprises such as dairy farming. Farmers with longer farming experience are at certain advantage that could be due to fixed transaction costs in production and marketing strategies, for instance transport and information search costs, hence efficient use of available inputs and higher levels of disposable income. There are no marked difference between in the statistics for most household characteristics, e.g. about equal mean and median figures for age, education, and farming experiences of household head.

Table 3. Description of variables and summary statistics for the sample of dairy households

Variable label	Variable description	Mean	SD	Min	Max	Median
CRS	CRS efficiency scores	0.39	0.31	0.001	1.00	0.29
VRS	VRS efficiency scores	0.49	0.32	0.002	1.00	0.41
SCALE	SE efficiency scores	0.78	0.22	0.077	1.00	0.84
AGEHH	Age of household head in years	49.95	15.08	18.00	100.00	49.00
FAEXHH	Farming experience of households head in years	24.59	15.70	1.00	75.00	22.00
FAMILY	Family size (adult equivalent)	4.91	2.12	0.82	14.25	4.57
EDUCATIONHH	Education level of house-hold head in years	6.84	4.57	0.00	25.00	7.00
FARM	Farm size in acres	101.91	488.67	0.25	7680.00	6.20
TLU	Number of cattle in TLU	17.16	28.64	0.70	277.20	8.20
RATIO_IMBRDS	Ratio of improved breeds	0.52	0.47	0.00	1.00	0.50
OFF-FARM	Off-farm employment	Yes =	192 (1)		No =	179 (0)
DAIRYCOOP	Member in a dairy coop.	Yes =	53 (1)		No =	318 (0)
ZERO_GRAZING	Practice zero grazing	Yes =	37 (1)		No =	334 (0)
FEED_CONSERVE	Conserve feed	Yes =	69 (1)		No =	302 (0)
LEGUMES	Grow fodder 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	Domains_HH: 155; Domains_HL 81; Domains_LH 33; Domains_LL 102				

Source: authors' calculation using survey data

The second category is related to farm assets; farm size, herd size (given in TLU) and the ratio of improved breeds to the total number of animals owned. Large farm and herd sizes are likely favor adoption of technologies that are likely to improve farm productivity. The results in Table 3 show considerable differences between the mean and median farm land size in acres as well as herd sizes measured in tropical livestock units (TLUs). This indicates the existence of a highly skewed farm size distribution. High social capital built through cooperative membership (NORTH, 1990), could influence adoption of new farm management skills that would lead to more efficient combination of inputs and outputs management practices including improving feed management. WAMBUGU et al. (2011) in their study on productivity trends and performance of dairy farming in Kenya also observe collective marketing through farmer cooperatives as an important ingredient to efficient performance of the small dairy enterprises especially those adopting zero-grazing system. Farmers can improve feed efficiency in order to enhance their gross margin rate of return. This can be achieved through various dairy management practices including improving feed management (WAMBUGU et al., 2011). This aspect is captured in this study using two dummy variables – conserve feed and grow fodder legumes. 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.

5.3 Econometric Results

Table 4 provides a summary of econometric results, which were separately estimated for Scale, CRS and VRS cases. The estimations were undertaken by log transforming all level form variables. These are mostly household characteristics including 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. Log transformation facilitates better estimate and interpretation for a wide range of meaningful, useful, and non-linear relationships between dependent and independent variables (HALVORSEN and PALMQUIST, 1980). It moves relationships from unit-based to percentage-based interpretations (LYLES, 2006).

Prior to running the model, a test was conducted to detect the problem of multicollinearity between variables included in the analysis. Distance from the farm to milk selling point, a variable that is considered important in market participation studies (MURIITHI and MATZ, 2014), was dropped as it depicted high tolerance and Variance Inflation Factor (VIF). The results of the rest of the variables used in estimation depicted no strong correlation since the values of the Variance Inflation Factor (VIF) are less than 10. Furthermore, the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) measures for model fit favoured the later model without distance to milk selling point. The qualitative information collected during the survey indicated that except farmers selling milk to cooperatives who delivered their milk at a designated point a distance away from the farm, other buyers collected milk at the farm gate. The model estimation is done using robust standard errors due to possible presence of heteroskedasticity.

Table 4. Results of the General linear model (GLM) with robust standard errors of factors influencing farm efficiency levels

Variable	*Scale*	*CRS*	VRS
Log (TLU)	-0.214* (0.125)	0.139 (0.110)	0.329*** (0.114)
DAIRYCOOP	-0.055 (0.256)	0.128 (0.245)	0.316 (0.236)
ZERO_GRAZING	1.261*** (0.362)	1.193*** (0.345)	1.067*** (0.335)
RATIO_IMBRDS	-0.050 (0.239)	0.299 (0.243)	0.446* (0.238)
FEED_CONSERVE	-0.234 (0.212)	-0.287 (0.220)	-0.199 (0.219)
LEGUMES	-0.088 (0.292)	0.642** (0.304)	0.989*** (0.334)
Individual customer dummy[1]	-0.131 (0.223)	0.377* (0.213)	0.638*** (0.233)
Private trader dummy	-0.517** (0.250)	-0.303 (0.223)	-0.025 (0.227)
Chilling plant dummy	-0.184 (0.273)	-0.140 (0.266)	-0.055 (0.258)
Uganda_dummy[2]	-0.056 (0.269)	-0.609** (0.299)	-0.611* (0.319)
Kenya_dummy	-0.060 (0.286)	-0.169 (0.350)	-0.205 (0.356)
HH dummy[3]	0.258 (0.224)	0.390* (0.233)	0.310 (0.248)
HL dummy	0.340 (0.257)	0.755*** (0.268)	0.627** (0.279)
LH dummy	0.376 (0.361)	0.206 (0.335)	0.050 (0.344)
Constant	3.390*** (1.294)	-0.479 (1.378)	-0.951 (1.414)
Number of observations	227	227	227
Deviance	51	83	90
Pearson	46	71	75
Log pseudolikelihood	-84	-112	-114
(1/df) Deviance	0.25	0.40	0.44
(1/df) Pearson	0.22	0.35	0.36
AIC	0.92	1.18	1.19
BIC	-1067	-1034	-1027

Note: statistically significant at 10% (*), 5% (**), and 1% (***); robust standard errors in parentheses [1]Dairy coop is the base; [2]Rwanda is the base country; [3]Domain LL is the base. The following variables are included in the above model but not shown since they are insignificant; *Log* (AGEHH), *Log* (FAEXHH), *Log* (FAMILY), *Log* (EDUCATIONHH), *Log* (FARM) and OFF-FARM

Source: authors' calculation using survey data

To begin with the scale efficiency, the results obtained for this model indicate that most variables in the category of household characteristics including education level and farming experience of the head of the household do not have statistically significant relationships with scale efficiency scores. This result is consistent with other findings in the literature that dummies representing household characteristics do not appear to be statistically significant to explain farm efficiency scores (ARMAGAN, 2008). Herd size measured in terms of tropical livestock units (TLU) is negatively related to scale efficiency and it is statistically significant at 10% (confirming what was previously discussed in relation to Figure 2). Off-farm income has positive coefficient and participation in dairy cooperatives has negative coefficient but both are not statistically significant.

By far the most important explanatory variable seems to be zero grazing, which has positive coefficient and it is statistically significant at 1% across the three efficiency measures. The other statistically significant coefficient is milk sales to private traders, which is negatively related to scale efficiency with statistical significance at 5% and the positive constant term with statistical significance at 1%.

Zero-grazing stands out as an important variable explaining efficiency score across all the three variables and at 1% level of statistical significance in each case. Apart from this, different variables appear to explain efficiency of the dairy farms under the scale, CRS and VRS. For instance, herd size measured in TLU is negatively related to scale efficiency (at 10% statistical significance) but it is related positively to VRS scores (at 1% statistical significance). This can be explained by the existence of positive relationships between TLU and the decreasing returns to scale (DRS) region of the VRS (as shown in Figure 1). Similarly, legume feeding and individual household as milk buyers appear to have positive and statistically positive relationships with CRS and VRS scores but these variables have negative signs under scale efficiency scores, although these relationships are not statistically significant.

It proves useful to ponder over this factor and provide further explanations for possible underlying causes that give rise to prominence of zero-grazing in smallholder farm efficiency analysis. Although they are not covered in the survey that provided the data used in this study, there are a number of explanations in the literature supporting, the findings related to zero-grazing in this study. The first one is related the role of zero-grazing in reducing “cow energy expenditure”. KAUFMANN et al. (2011) employed a sophisticated laboratory based experiment and established that free grazing means dairy cows spend a good proportion of energy on locomotion to move in pasture fields. On the other hand, zero-grazing does not require such movements and hence the bulk of energy obtained from feed get converted to milk. The efficiency gain is the net outcome of positive contribution of zero-grazing to greater volume of milk (and hence farm income) and its requirement for more labour to cut and carry grass to the feeding lot. The findings in this seem to indicate that the revenue gain outweighs the labour costs.

The second category of explanation seems to lie in the fact that zero-grazing enables farms to realize full potential of farming plots. First, milk yield per unit area of land is higher for zero-grazing dairy farms compared free grazing farms, as GARCIA et al. (2008) explains using data from Uganda. Given that zero-grazing means keeping dairy cattle in a small feeding lot, the fact that less land is required per cow may sound an obvious point. However, there are much deeper ways in which milk yield and land productivity re-inforce each other. In the first instance, it should be noted that, unlike dairy farming in developed countries where intensive dairy farms rely on concentrates, zero-grazing rural East Africa is largely practiced through "cut-and-carry system" – farmers cut pasture, legumes, or other feed types from the field and bring to the feed lot.

Critically, a farmer is likely to produce much larger volume of biomass of grass from a given plot of land with zero-grazing than with free grazing. The reason is that free grazing means cows walk in the fields often repeatedly on the same spot, this leads to stampede that leave grasses with less and less opportunity to regenerate. Additionally, using a case study in Uganda, ZIMBE (2012) found out that greater amount of manure can be collected through zero grazing than free grazing. The collected manure can either be sold (additional output and hence farm income) or it can be used on the farm leading to improvements in land productivity to produce greater volume of biomass of crops or feed plants.

The lower part of Table 4 display model fitness statistics which are useful indicators to choose from the three alternative models for explaining dairy farm efficiencies. Given that the Scale, CRS and VRS models were estimated with the same sample size and equal number of parameters, the Akaike's Information Criterion (AIC) and the Bayesian information criterion (BIC) provide sufficient statistics to select from these models (BURNHAM and ANDERSON, 2004). These statistics assesses the overall fit of a model and allows the comparison of both nested and non-nested models. The model with the lowest AIC statistics fits the data much better than alternative models. On the other hand, if the BIC is consistently negative, then the model with larger negative BIC (with larger absolute value) is preferred to alternative models. Both the AIC and BIC tests indicate that estimates obtained using scale efficiency fit the data sufficiently better to justify the number of parameters that are used in the model than those under CRS or VRS. This result is consistent with findings elsewhere – JAFORULLAH and WHITEMAN (1999) on New Zealand dairy and GRAHAM and FRASER (2003) on Australian dairy – that scale inefficiency is a significant contributor to overall inefficiency in dairy farms.

6 Conclusions

The study measured, decomposed and explained returns to scale indicators in dairy farms sampled from seventeen districts in three East African Countries. Farm efficiency scores were obtained by applying the linear programing based DEA methodology. The optimization technique generated efficiency scores corresponding to different returns to scale. The distribution of these efficiency scores were then presented and discussed.

The distributions of different efficiency scores indicated that dairy farms in the region are operating at low level of efficiency. About 27% (or 101) farms are characterized by CRS which means that they can change scale of operation by proportionately increasing or decreasing input-output combinations. On the other hand, the majority of the farms (71%) are characterized by IRS. This implies that the dairy farms can gain efficiency by increasing production and become scale efficient. On the other hand, a small number of units (7 farms) were found to be operating in the DRS range, which means they would need to reduce scale of operation to gain efficiency improvements.

The analysis of farm size measured by TLUs and scale efficiency scores revealed that the smallest size band of less than 5 TLUs have an average efficiency score of 0.87 scale efficiency score but farms in larger herd size bands (of 45-50 and > 50 TLUs) have average efficiency score of 0.53 scale efficiency scores. This indicates that the former group is about 34% more efficient compared to the latter group. This confirms the existence of inverse relationships between farm size and farm efficiency.

The second stage dairy farm efficiency analysis was conducted using econometric methods to explain variations in difference returns to scale scores among the farming units. In order to see their differences in fitting the data, the econometric estimation were separately conducted for the CRS, VRS and SE scores separately. By far the most important explanatory variable was zero grazing, which has positive coefficient and statistically significant at 1%. The other statistically significant coefficients are milk sales to individual traders which is negatively related to scale efficiency with statistical significance at 5% and the positive constant term with statistical significance at 1%. Zero-grazing stands out as an important variable explaining efficiency score across all the efficiency score categories (CRS, VRS and SE) and at 1% level of statistical significance in each case. The fitness test using AIC and BIC criteria indicated that the SE based model fits the data better than the CRS and VRS models. This indicated that scale of operation is the main source of inefficiency among dairy farms in the region.

The fact that the SE model emerged as a preferred model has far reaching policy implications. First, the descriptive analysis in earlier section of the study showed inverse relationship between herd size and dairy farm efficiency (as shown in Figure 2). Second, in the econometric analysis, herd size (measured in TLU) has a negative and inverse relationship with scale efficiency scores. Third, statistical tests of model selection criteria indicated that scale efficiency based model is the most preferred one compared to the alternative models. The combined outcomes of these empirical evidences suggest that policy makers and donors have to pay specific attention to scale of farms in the context of East Africa. In other words, encouraging reductions in herd sizes and then focussing on improvements in management of the small dairy farm units will enhance dairy farm efficiency in the region. The emergence of zero-grazing as a key determinant of dairy farm efficiency is an element of scale issues that need to be taken seriously in formulating policy-making, specifically for dairy farms in East African countries.

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