Farm Size, Modern Technology Adoption, and Efficiency of Small Holdings in Developing Countries: Evidence from Kenya

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FARM SIZE, MODERN TECHNOLOGY ADOPTION, AND EFFICIENCY OF SMALL HOLDINGS IN DEVELOPING COUNTRIES: EVIDENCE FROM KENYA

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ABSTRACT

Low efficiency is a problem in most developing agriculture, and is one of the reasons for food insecurity. This paper provides information on smallholder production efficiency in one of the developing Sub-Saharan Countries: Kenya. It applies Data Envelopment Analysis (DEA) to farm-level seasonal panel data. The estimated indexes indicate high levels of inefficiency between farm sizes, seasons, and adopters and non-adopters of 'modern' farming technologies. A comparison of various farming practices shows that use of modern inputs and livestock-based capital could significantly improve farmers' performance. Tobit estimations show that the major factors influencing performance are the level of education, gender, market access and off-farm capital. Thus, policies aimed at improving education, rural infrastructure as well as assuring farmers of income through improved livelihood opportunities, and therefore reduced perceived uncertainty, could improve farm-level efficiency. The findings also provide support for prioritizing issues of farm production associated with women in policymaking.

JEL Classifications: C23, D13, D24, O13, Q12, Q16
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INTRODUCTION

Evidence abounds that agricultural production systems in Sub-Saharan Africa (SSA) are still characterized by low efficiency and productivity, although a few studies have reported isolated cases to the contrary (Hyden, 1986; Nyariki and Thirtle, 2000; Thirtle et al., 1993; Wiggins, 1995). The low efficiency and productivity growth in smallholder agriculture in SSA is manifested in the cumulative discrepancy between African production rates and those of the rest of the world.

In the case of Kenya, the country experienced a rapid expansion in agricultural production whose contribution to GDP grew by more than four percent in the first decade. The introduction and widespread adoption of new technologies led to a steady increase in food production. These developments, however, slowed down after the early 1970s (ROK, 1994; Nyariki, 1997). Because of this, government objectives during the 1970s and 1980s were geared towards increased food production from less productive lands, growth in agricultural employment, and resource conservation to improve food security.

The poor performance of agriculture in Kenya reflects a serious problem because this sector is the mainstay of the economy. The sector accounts for approximately 25 percent of GDP, provides employment for close to 70 percent of the population, contributes roughly 40 percent of export earnings, and provides most of the country's food supply (ROK, 2008). Slowing growth rates coupled with high population growth and limited arable land raise serious questions as to how this sector will meet the challenges of sustained per capita growth.

Kenya's past development plans have proposed to reduce the area under food production in order to release land to more valued export crops, which would then improve the per capita value of agricultural production. This meant that increases in the basic foodstuffs had to come from higher yields, and by implication higher efficiency of farm resource use. However, the efficiency of smallholder farms must first be enhanced to optimize the returns from the use of enhanced technology.

The lack of adequate information on the patterns and sources of efficiency of smallholder farms has become an important issue because the country faces household food insecurity (Nyariki et al., 2002). Thus, this paper analyzes the efficiency of smallholder farms and the factors influencing efficiency in one of the medium to low potential areas of Kenya. The next section briefly describes the farming area, followed by details of how data were collected and the variables used. The next section outlines the model used to derive efficiency indexes and discusses the results at this stage. Finally, the factors affecting efficiency are identified through Tobit regressions and the results are compared to those of similar studies in other developing countries.

FARM CONDITIONS IN THE SAMPLE REGION AND DATA

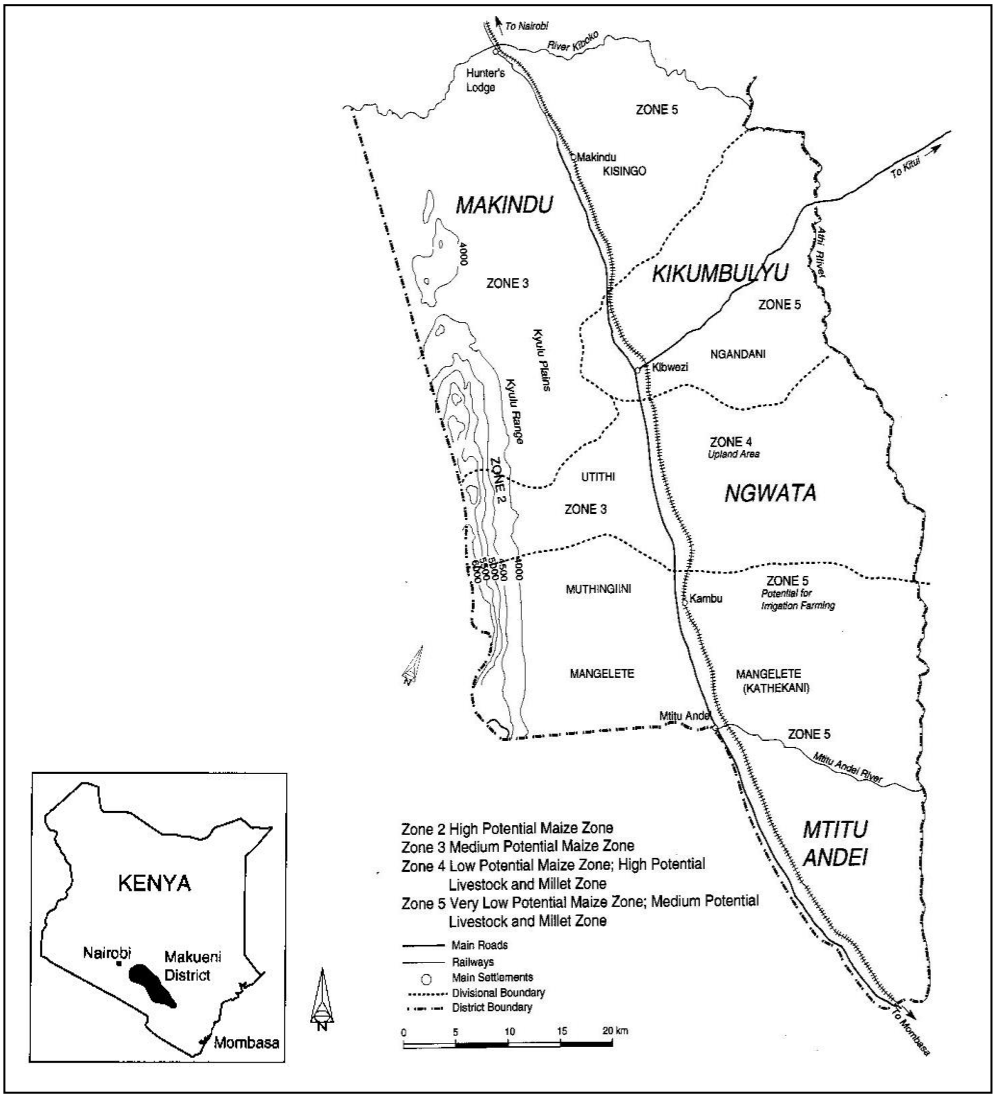
The sample was taken from farms in Kibwezi Division of Makueni District, in the south-east of Kenya. This is a semi-arid area with an average annual rainfall of between 600 and 1300mm, occurring in two seasons—March to May and October to December. Annual mean temperatures are 19–26^{0}C, which increase with evaporation down-slope. The study region is classified into six agro-ecological zones (AEZs); the most dominant of which are AEZs 3, 4 and 5 (Figure 1).

The region lies east of the Great Rift Valley covering about 7,263 km^2 (ROK, 1994). It has an estimated human population of over 500,000, giving a density of about 70 persons per km^2 (ROK, 2008). Settlements in the area are recent (circa 1970). FAO (1982) recommends areas like this to support 21 persons/km^2 at full-potential. This suggests that the area is overpopulated, and would therefore require improved efficiency of resource use, among other measures, to ensure adequate food production.

The land has great potential for sorghum, millet, cotton, sisal and livestock production, as suggested by the agro-ecological zones shown in Figure 1. Furthermore, Athi River, a major water resource in the area, makes it possible for crop irrigation and improved livestock production.

Systematic sampling was done using a sampling frame constructed from all the available households of more than 1,000, from which 50 households were selected. Systematic sampling is often necessary, especially in a developing country like Kenya, due to poor infrastructure and difficult terrain (Nyariki, 2009). After selecting the sample, interviews were carried out using a questionnaire. Households were visited three times to obtain data for the three seasons of 2006-2007-2008. During the interviews, all the farmers selected gave adequate responses for analysis.

FIGURE 1. STUDY REGION SHOWING AGRO-ECOLOGICAL ZONES



Source: Adapted from Sombroek and Braun (1980).

Table 1 gives some sample statistics. Underlying these are average maize yields which for the three seasons were 1083kg, 70kg and 781kg respectively. This variation was reflected in other crops, a clear indication that yields follow fluctuating rainfall. The table reports annual maize and total crop yields per household in terms of users and non-users of various farm inputs, where yields are obtained by aggregating all crops into maize-equivalents using average prices as weights over the three seasons. Generally higher yields were realized with the use of modern inputs, irrigation and the ox-plough.

TABLE 1. USE OF VARIOUS INPUTS AND ANNUAL AVERAGE YIELDS (KG/HA) IN KIBWEZI (2007/08)

Household category	Maize		Maize-equivalents	
	Use	Non-use	Use	Non-use
Hybrid seed	757	794	963	825
Fertilizer	821	772	907	872
Pesticide	862	770	1399	820
Irrigation	811	546	896	746
Ox-plough	783	767	835	1012

DATA ORGANIZATION

Aggregation of Inputs and Outputs

The approach normally taken in constructing a benchmark of good practice involves defining the practitioners' objectives, defining inputs and outputs, evaluating the possible output with that level of input, and measuring the difference between the two. The vexing question in these estimations has been determining the method and extent of output and input aggregation, the *á priori* selection of inputs, and the unit of measurement.

Various methods of aggregation have been adopted in this literature. Some studies have used a mix of physical and monetary measures (for example, Byrnes et al., 1987), while others have applied gross monetary values singly (for example, Langyintuo and Upton, 1994). Other studies have concentrated on a dominant crop and ignored the less important ones (for example, Piesse et al., 1996). If the choice is physical units of a major crop, the terms of trade of that crop with available alternatives must be known. If households cultivate a constant number and/or variety of crops on the same land or on distinctly different plots, a multi-product, multi-input analysis could be adopted. Applying monetary values in a situation where the primary objective is to produce for subsistence may, however, be misleading. Moreover, even if the primary objective was to produce for the market, the price obtained is as much a function of the market structure and marketing strategy as it is an economic concept of profit maximization. Thus, the use of prices as weights to aggregate outputs and inputs in any study of African agriculture can have limitations, and the robustness of the method of aggregation may determine how accurately the efficiency indexes derived reflect the performance of individual farmers.

Schultz (1964) presents a less pessimistic view of the value of prices in aggregation, claiming that small farmers in traditional agriculture are well informed about the price in various markets. They are familiar with the local rents and are shrewd participants in the marketplace. There is therefore strong support for the view that food production in Africa is responsive to market forces (Berry, 1986; Wiggins, 1995; Mwakalobo, 2000), providing sufficient justification for the price-weight aggregation used in this efficiency measurement.

Selection of Inputs and Outputs

A summary of the variables used in the construction of efficiency levels is given in Table 2. The inputs are: (1) land (hectares); (2) total labor (household and hired in adult-hours); (3) cost of manure and seed, including modern inputs (improved seed, fertilizer, pesticide), costed whether bought or not using the average prices paid for them locally, as reported in the survey; (4) cost of capital (ox-plough, tractor, and miscellaneous inputs); and (5) livestock (aggregated into livestock units). Prices were used in aggregating some inputs if no suitable physical units were available, and also because some of the input use was so minimal that no suitable physical units were available.

TABLE 2. SUMMARY STATISTICS OF VARIABLES IN EFFICIENCY MEASUREMENT

Variable	Sample mean	SD	Minimum	Maximum
Value of output (Kshs)				
Season 1	24744.0	18691.5	967.2	62961.4
Season 2	6824.8	9093.7	5566.4	18652.7
Season 3	20629.0	13365.6	7755.3	33776.8
Farm size cultivated (ha)				
Season 1	4.7	2.4	1.3	9.8
Season 2	4.0	3.0	0.6	7.6
Season 3	4.5	2.7	0.9	8.2
Total labor (adult-hours)				
Season 1	2843.0	1267.0	88	15811
Season 2	1947.2	1658.7	40	11914
Season 3	1992.8	1758.8	66	10143
Cost of inputs (Kshs)				
Season 1	1226.0	1463.4	350.4	6206
Season 2	858.4	923.9	240.5	5345
Season 3	1062.4	1075.9	320.6	6747
Cost of capital (Kshs)[1]				
Season 1	2019.0	2043.4	0	4319
Season 2	1040.9	1280.0	0	2243
Season 3	1800.0	2063.6	0	3916
Livestock (250kg/unit)				
Season 1	8.6	7.9	0	21.9
Season 2	8.2	9.5	0	20.0
Season 3	5.8	7.8	0	14.0

All farm outputs were aggregated to derive a single unit. However, live animal sales (off-takes) were excluded because of difficulties in interpretation.[2] An average of the buying and selling prices of the relevant crops and animal products by households in each season was used in constructing efficiency measures, as this is a more consistent estimate of price than either buying or selling price individually.

MEASUREMENT OF PRODUCTIVE EFFICIENCY

The Advantages and Disadvantages of the Various Frontier Models

The DEA and Corrected Ordinary Least Squares (COLS)—using a translog function—are the most popular methods applying physical measures of inputs and outputs to derive indices of performance (Cloutier and Rowley, 1993; Cowie and Riddington, 1996; Amara et al., 1999; Wadud, 2003). The DEA model was initially developed by Charnes, Cooper and Rhodes (CCR) (1978)—and applies linear programming (LP) to estimate an empirical production technology frontier. The model was further formalized by Banker, Charnes and Cooper (BCC) (1984). It was later extended by Färe, Grosskopf and Lovell (1985) to include the decomposition of overall efficiency into measures of technical and scale efficiency. It is nonparametric and deterministic, with the efficiency of each farm measured as a ratio of actual to best practice performance. Thus, since the seminal work by Farrel (1957) on 'measuring the efficiency of decision making units', several models of the DEA have emerged with the most basic being the CCR. A further development on the DEA is the BCC model, which addresses varying returns to scale—either constant returns to scale (CRS) or variable returns to scale (VRS). A good description of DEA can be found in Seiford and Thrall (1990) and Seiford (1996).

With the adoption of the translog function, the main disadvantages are the difficulty in interpreting the coefficients estimated and the using up of a large number of degrees of freedom relative to the number of factors included in the estimation of parameters.[3] The DEA has many advantages but its main attraction, compared to most forms of stochastic frontier analysis (SFA), is that no functional forms are imposed; so it does not matter if the producers differ. The problem regarding the assumption of identical production technology for all decision making units (DMUs) in the SFA has, however, been circumvented by new theoretical developments in the application of the true-random-effects (TRE) model (Greene, 2005).

The difference between the SFA and the DEA is the latter's ability to decompose technical efficiency into overall technical, pure technical and scale efficiency. One shortfall of deterministic models is that they fail to deal with stochastic noise, which might result in efficiency levels being 'systematically' overestimated. This tendency to overestimate efficiency scores does not present a problem in the current study, however, as long as it is 'systematic overestimation', which should not fail to answer the key research question—whether or not 'season, farm size and modern technology adoption influence smallholder production efficiency'.

Specification of the Applied Model

The DEA model adopted in this paper uses the VRS approach. Based on the extensions on the BCC model by Färe, Grosskopf and Lovell (1985), (overall) technical efficiency, $OT(x,y)$, can be decomposed into pure technical efficiency and scale efficiency—where x stands for the input(s) used and y output(s) produced. Let pure technical efficiency and scale efficiency be denoted by $PT(x,y)$ and $S(x,y)$ respectively. To estimate these measures the restrictions imposed on the reference technology in the aggregate measure of efficiency $OT(x,y)$ are relaxed. Overall technical efficiency can be expressed as

$OT(x,y) = PT(x,y) \cdot S(x,y)$

The efficiency measure $PT(x,y)$ can then be expressed as

$$PT(x,y) = \min\{\theta : \theta x \in L(Y)^{+}\} \quad (1)$$

where $L(Y)^{+}$ represents the upper level set of the reference technology, i.e., the lower boundary of the isoquant which shows minimal input combinations yielding a given level of output Y. θ is the minimized parameter and determines the amount by which observed inputs can be proportionally decreased if they can be used efficiently. The input usage, x, is an element of the upper level set, $L^{+}(Y)$. When θ is minimized, θx lies on the isoquant.

The technology in (1) allows $PT(x,y)$ to be estimated without imposing constant returns to scale, but instead allows for variable returns to scale. The VRS technology gives efficiency measures independent of scale effects. The CRS restriction is relaxed by changing the restriction on the vector of intensity parameters, z, so that we have the following linear programming problem:

$PT(x,y) = \min\theta$
subject to $zY \geq y_i$*
$zX \leq x_i$**
$z_i \geq 0$
$\sum z_i = 1$***

where i denotes the observation. The extra constraint on the z vector *** (the sum of z's=1) allows the data to be enveloped more closely and permits VRS to be exhibited (Valdmanis, 1992). Once $OT(x,y)$ and $PT(x,y)$ efficiency measures have been obtained, the $S(x,y)$ measure is derived by using the following equation:

$S(x,y) = OT(x,y)/PT(x,y)$

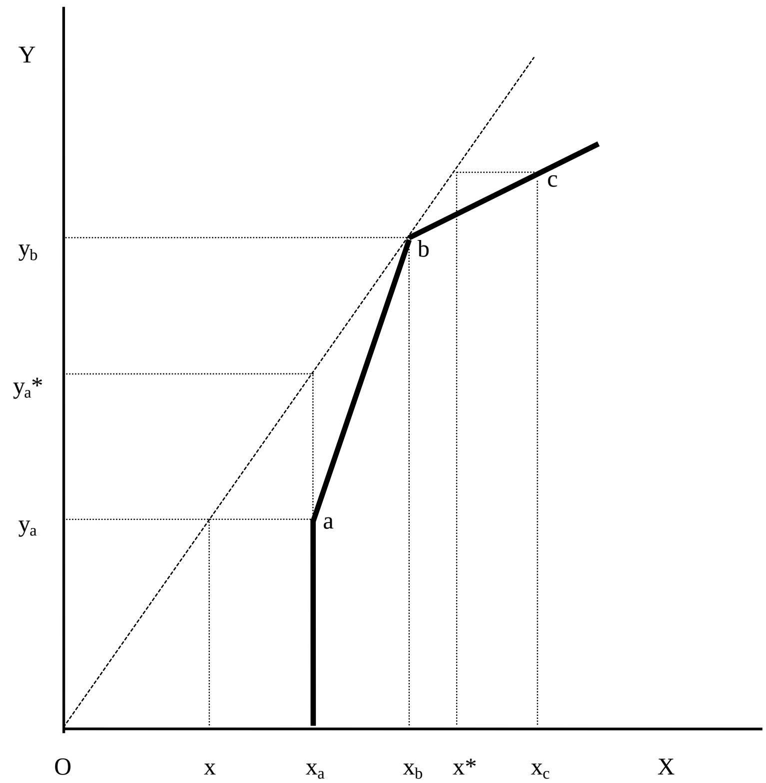
Figure 2 illustrates the VRS technology using a total product curve. Suppose there are three farms, *a*, *b* and *c*, which employ input X to produce output Y with three different input-output combinations. The transformation *a-b-c* exhibits CRS at *b*, increasing returns to scale (IRS) between *a* and *b* and decreasing returns to scale (DRS) to the right of *b*. With CRS technology, farm *a*, which employs x_a of input X, is overall technically inefficient because it produces output y_a instead of its potential y_a*. Farm *b* is overall technically efficient as it lies on the potential total product curve, which is a ray from the origin derived from average product *x/y*. In measuring the scale efficiency, the long-run equilibrium condition, which is constant returns to scale, is assumed to represent optimal scale. To determine whether a given observation is scale efficient (i.e., satisfies CRS), the original transformation set (ray from the origin) which exhibits CRS everywhere must be modified (to, for example, x_a-*a-b-c*) to allow for IRS as well as DRS. The economic interpretation of the shape of the VRS technology is based on the omission of the scale effects on overall efficiency (Valdmanis, 1992). Farms *a* and *c* become efficient since they lie on the new transformation set, and therefore exhibit a best practice technology. Therefore all the three farms are efficient given the VRS technology. The difference between the CRS and the VRS frontiers captures the scale effects. Farm *a* is scale inefficient by ox/ox_a and farm *c* is scale inefficient by ox^*/ox_c (Thirtle *et al.*, 1996).

INTERPRETATION OF EFFICIENCY RESULTS

Seasonal Differentiation

Table 3 gives a summary of efficiency measures for the three farming seasons—second season of 2006/07 (season 1), first season of 2007 (season 2) and first season of 2007/08 (season 3). (Farm-level results can be provided if requested.) The efficiency scores are grouped based on farm characteristics using farm-level data collected from the sample of 50 households during the questionnaire survey.

FIGURE 2. VARIABLE RETURNS TO SCALE



The efficiency measures are highest in season 1 and then progressively decline. Sixteen farms (32%) are overall technically efficient in the first season, declining to 16% in the more risky season 2, and further to 6% in season 3. The dispersion levels are fairly constant, which implies that weather, exogenous to all farms equally, may in part be responsible for falling efficiency. The decomposition of overall technical efficiency into pure technical efficiency and scale efficiency shows a similar pattern.

The means of the indexes in Table 3 indicate that factors of inefficiency caused output losses of 58%, 83% and 88% in overall technical efficiency; 44%, 48% and 62% in pure technical efficiency; and 24%, 65% and 69% in scale efficiency in the three consecutive seasons respectively.

TABLE 3. SUMMARY STATISTICS OF EFFICIENCY MEASURES BY INPUT USE, SIZE, TECHNOLOGY ADOPTION AND SEASON

Category of farms	Season 1			Season 2			Season 3		
	OT	PT	S	OT	PT	S	OT	PT	S
Mean, whole sample (50) farms	0.42	0.56	0.76	0.17	0.52	0.35	0.12	0.38	0.31
Hybrid seed	0.73	0.83	0.88	0.14	0.51	0.27	0.14	0.53	0.42
No hybrid seed	0.24	0.37	0.65	0.22	0.52	0.45	0.12	0.27	0.23
Plough	0.75	0.84	0.87	0.13	0.54	0.35	0.26	0.61	0.50
No plough	0.24	0.37	0.66	0.22	0.49	0.35	0.14	0.23	0.20
Fertilizer	0.85	0.88	0.85	0.10	0.43	0.32	0.28	0.58	0.48
No fertilizer	0.29	0.41	0.69	0.29	0.62	0.38	0.23	0.38	0.27
Cattle	0.65	0.75	0.88	0.21	0.68	0.46	0.16	0.48	0.45
No cattle	0.34	0.46	0.65	0.20	0.39	0.27	0.15	0.34	0.22
Irrigation	0.54	0.66	0.84	0.46	0.80	0.63	0.28	0.63	0.43
No irrigation	0.38	0.51	0.68	0.25	0.40	0.27	0.14	0.30	0.29
Small*	0.46	0.54	0.76	0.20	0.55	0.41	0.16	0.36	0.34
Large	0.40	0.61	0.76	0.18	0.50	0.34	0.13	0.42	0.31
Modern**	0.52	0.66	0.88	0.16	0.50	0.34	0.12	0.40	0.33
Traditional	0.42	0.50	0.64	0.18	0.56	0.35	0.14	0.40	0.30
Frontier farms (%)									
Whole sample	32	40	32	16	20	16	6	12	6
Modern	24	30	24	2	4	2	4	8	4
Traditional	8	10	8	14	16	14	2	4	2

**Small farms are >0≤4ha while large farms are >4ha.*
***In each season, 'modern' technology adopters used one or a combination of the three inputs—hybrid seed, fertilizer and plough—while 'traditional' farmers used none of them.*

If performance is compared between farmers, the best farmers were between 76.1% and 99.7% more efficient than the least efficient ones. The best were also between 20.5% and 75.3% more efficient than average. In each of the three seasons, farm size is an important limitation, and 25-50% more farmers achieve pure technical efficiency than overall efficiency. The mean of the land variable does not change much between seasons. Farmers use their experience from the previous years and know there is a higher probability of crop failure in season 2. Clearly, farmers try to minimize risk; they use lower levels of inputs in this middle season to avoid incurring large losses in the event of crop failure. This results in more farms being full-efficient in season 1 compared to the other seasons. However, since each frontier is independent of the others, it means that a poor season due to low rainfall should affect all farms equally; but this was not the case probably because many farmers were risk averse. Carry-over seasonal effects may be existing and tests for the significance of these are in a later section.

Analysis of Farmers by Specific Practice and Size

The assumption of homogeneity of DMUs is required to make judgment on performance based on methods founded on peer comparisons. But there is never a system that can be perfectly homogeneous. Thus, we have to relax the condition to accept a reasonable degree of homogeneity, although the 'reasonable degree' may be difficult to discern. The contradicting argument regarding efficiency analysis is that if perfect homogeneity were to be achieved, it would render the exercise of comparing operators meaningless, as everybody becomes efficient. This is the cyclical argument concerning the definition of efficiency.

The efficiency indexes were regrouped into those that used modern inputs and those that predominantly used traditional farming technology, among others (Table 3). On average, those farmers that were technically efficient owned cattle, carried out chemical fertilization of their fields, and had some access to irrigation water. Most of the farmers reported having used part of their crop as fodder. During anticipated crop failure, the farmers would cut the green maize or sorghum stock as feed for the animals. Apparently these farmers were experiencing the benefit of crop-livestock interaction whereby livestock provided manure for cropping and crop aftermath provided fodder for livestock.

On average, those farmers who had practiced irrigation achieved higher efficiency levels. Needless to say, this result implies that provision of extra water is crucial in low to medium potential areas as it would raise performance through increased farm and animal production, by lengthening the growing period or reducing plant and animal water stress.

The results for seasons 2 and 3 appear to be different from those for season 1. These were seasons of prolonged dry weather. During this period the rains were so slight the only crops realized were the legumes that have some degree of tolerance to water stress. Those farmers who had purchased expensive inputs experienced great losses in cash. In contrast, those farmers that had used little or no such inputs lost comparatively little. Related to this, characterization of farmers into modern and traditional indicates that greater efficiency tends to be achieved among farmers who use one or other of the modern inputs during normal rain season. During the low rain seasons, however, traditional farmers perform better (Table 3).

Further categorization of farmers into small and large shows that in the normal season better performance was realized among the larger farms while the opposite was true during the drier seasons. Generally, however, the differences in this category are not pronounced.

Seasonal Distribution of Efficiency

The distribution of the three measures of efficiency for the three seasons was compared to assess the stability of the efficiency measures from season to season, after which a decision could be made on whether to carry out further tests concerning efficiency determinants using the entire data set. Without stability it would not be sensible to pool the data, as efficiency among farmers would not be enduring. Table 4 reports the results using a variety of methods for comparison. The model underlying the parametric methods assumes that the data have been derived from normal distributions with equal variances. Assuming the condition of normality might not be fully realized, nonparametric methods are used as suitable alternative sources of information about the distribution of the efficiency indexes. The ANOVA tests whether there are significant differences between data sets, while the Spearman rank correlation coefficient tests whether there is agreement between rankings. The null hypothesis is that the distribution of efficiency in one season is independent of that in the other season. The results generally show that the null hypothesis is rejected. Therefore there is no difference in index means between seasons and the indices are not independent.

TABLE 4. STATISTICAL TESTS: COMPARING EFFICIENCY MEASURES BY SEASON

Seasons compared	Efficiency measure	ANOVA (F) (Prob.>|F|)	Spearman
Season 1/season 2	OT	0.112 (0.739)	-0.021 (0.890)
	PT	0.045 (0.833)	0.005 (0.974)
	S	0.143 (0.707)	-0.097 (0.502)
Season 1/season 3	OT	1.842 (0.181)	0.146 (0.312)
	PT	6.053 (0.018)*	0.213 (0.138)
	S	0.452 (0.505)	0.107 (0.458)
Season 2/season 3	OT	2.134 (0.151)	-0.091 (0.528)
	PT	0.271 (0.605)	0.034 (0.816)
	S	2.342 (0.133)	-0.075 (0.606)

**P-values (in brackets) significant at 5% level for two-tailed test*.

DETERMINANTS OF EFFICIENCY

Variables

This section explains farm efficiency using household characteristics, infrastructure and farmer decision variables. Table 5 provides summary statistics for the variables. The variables were constructed from the data collected from the questionnaire survey. These variables included household size—all members resident in the farm within the season; level of education in four categories—the absence of formal education earning the lowest score of 1 while secondary and college education the highest of 4; farm size—area of land used; level of development or quality of infrastructure and marketing system (represented by the approximate distance from the homestead to the nearest market place); age of farmer (based on ranges); number of sources of income (diversification); planting time—in four categories (those planting weeks before rains scoring the lowest while those planting weeks after the highest); gender of household head (female=0, male=1); and extension (number of visits in each season).

TABLE 5. DESCRIPTIVE STATISTICS OF VARIABLES IN THE ANALYSIS OF DETERMINANTS OF FARM EFFICIENCY

Variable	All seasons		Season 1		Season 2		Season 3	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age of farmer (years)	47.99	15.2	47.96	14.1	47.96	14.6	48.11	15.5
Gender of household head	0.64	–	0.68	–	0.66	–	0.62	–
Farm size (ha)	4.42	2.8	4.72	2.4	4.06	3.0	4.55	2.7
Household size	7.32	2.3	7.32	2.5	7.40	2.6	7.26	2.4
Level of education	1.68	–	1.62	–	1.66	–	1.70	–
Market distance (km)	3.16	1.2	3.22	1.1	3.18	1.0	3.04	0.9
Number of income sources	2.85	1.5	3.05	1.8	2.52	1.4	3.10	1.5
Technical advice	0.30	–	0.28	–	0.26	–	0.32	–

Note: Sample size=50.

A Two-tailed Tobit Using Panel Data

The Tobit approach has been used in several studies to evaluate the factors influencing farm inefficiencies and technology adoption (e.g., Fernandez-Cornejo, 1994; Wadud, 2003). As an example, Wadud (2003) carried out a Tobit regression analysis on both stochastic frontier and DEA efficiency scores to determine the factors associated with inefficiency of farms in Bangladesh. In this analysis, there was no overall difference between the results related to the stochastic frontier and DEA scores.

Various parametric approximations of non-parametric frontiers have been proposed in the recent literature. One of these is a bootstrap approach to deal with the stochastic noise in non-parametric frontiers (Simar, 1992). However, as Simar himself admits, these approaches have no theoretical and statistical background (Simar, 2003). Thus, this paper does not attempt to adopt these approaches.

In the Tobit analysis, the three seasons were combined to form a panel of data, increasing the degrees of freedom and ensuring the robustness of the estimates. Since efficiency indices are bounded between zero and one, the dependent variable is limited, and therefore the use of OLS regression is inappropriate as the residuals do not satisfy the condition $E(\mu_t) = 0$, which is required to derive unbiased estimates (Maddala, 1988). The likelihood term for the efficiency is given by the integral from $-\alpha_i - \beta X_{it}$ to $1 - \alpha_i - \beta X_{it}$. Parameters are then obtained through maximum likelihood estimation (MLE) by applying a two-tailed Tobit procedure (Baltagi, 1995; Fernandez-Cornejo, 1994). The base regression equation for this purpose is:

$$Y_{it} = \alpha_i + \beta X_{it} + \mu_{it} \qquad (2)$$

$i = 1, 2, ..., N$
$t = 1, 2, ..., T$

where Y_{it} is the efficiency measure for the ith farm in the tth period (season) and X_{it} is a k-dimensional vector of observable variables, α_i captures the farm specific unobserved variables, ß is a k-dimensional vector of parameters, and μ_i is the error term with mean zero and variance σ^2 representing unmeasured or un-measurable variables influencing farm efficiency.

A common approach to represent unobservable units in analyses of panel data involves the use of a varying intercept term. Under this approach, the equation in (2) is transformed to allow the intercept term to differ according to the unobserved differences for each cross-sectional unit, giving the fixed effects model (FEM):

$$Y_{it} = \overline{\alpha} + \gamma_i + \beta X_{it} + \mu_{it} \qquad (3)$$

where $\overline{\alpha} + \gamma_i$ is the intercept for the *i*th farm and $\overline{\alpha}$ is the mean intercept. The appropriate estimation procedure depends upon the cross-sectional effects γ_i. If the effects are fixed, then a standard dummy variable model is appropriate; if they are random, error components estimation procedures should be used. The choice is important because if the effects are fixed, use of a random effects model (REM) will produce biased parameter estimates while, if the reverse is the case, use of a FEM will yield inefficient estimates (Maddala, 1988; Pindyck and Rubinfeld, 1991). A statistical test for the correct specification of such cross-sectional effects has been developed by Hausman (1978).

Results of the Analysis of Efficiency Determinants

Table 6 reports the Tobit estimation. The factors that have a significant effect on efficiency are consistent and the signs are as expected. Education has a significant positive influence on the farmer whilst age has an opposite response. This is the expectation because it is likely that a more educated farmer understands faster any new innovation. These results support the premise that increases in human capital enable households to improve resource utilization and thus achieve higher productivity.

Planting time has a negative effect. Farmers that planted just after rains had higher yields, a result that supports the view that efficiency is a function of rainfall. Diversification (off-farm income and remittances) has a significant effect on efficiency and extra cash increased the use of modern inputs. Infrastructure is important if produce is to be sold. The negative and significant coefficient on the distance to market indicates that those closer to markets are more efficient. Part of the reason is access to transportation, but also the more remote lose out in the exchange of ideas and opportunities to learn new techniques.

Farm size, if land is not limited, depends on the availability of labor. Household size plays a major role in determining the number of those available for work. However, the two size variables have a limited influence except on scale efficiency. This finding is contrary to what is commonly believed; that in much of rural Africa labor rather than land is a more important constraint to farm production (Upton, 1987). The outcome of this analysis is not surprising. If larger households apply more labor, it is possible that the marginal product of such labor declines, making the farms in question a little less efficient than the rest in the sample.

Finally, the gender variable influences efficiency negatively, suggesting that female-headed households are more efficient than their male counterparts. The likely reason is that women are more involved in making decisions about farming and are therefore better innovators. However, several similar empirical studies have reported an opposite effect (e.g., Solis et al., 2009; Gonzalez, 2004). These studies contend that lower

TABLE 6. TOBIT ESTIMATION: FACTORS INFLUENCING EFFICIENCY

	OT		PT		S	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
Constant	2.456	1.44	2.18	1.83	0.59	-1.22
Age of farmer	-0.187	-2.16*	-1.342	-1.99*	-1.46	-2.21*
Gender of household head	0.105	-1.99*	1.015	-2.44*	0.117	-2.84*
Farm size	0.012	-1.23	0.225	-1.05	0.743	2.12*
Household size	0.513	-1.74	0.188	-1.85	1.344	1.97*
Level of education	0.146	1.98*	0.161	2.25*	0.160	2.00*
Market distance	-0.741	-4.14*	-0.111	-2.14*	-0.416	-3.35*
Number of income sources	1.006	2.32*	1.354	2.18*	1.752	2.55*
Technical advice	1.512	1.89	1.125	1.92	0.422	1.96*
Time of planting	-1.961	-2.70*	-1.949	-2.32*	-1.019	-1.89
χ^2 test - joint effect variables	42.91*		43.14*		59.09*	
F-test for fixed effects	5.99*		8.37*		8.87*	
Hausman test statistic	69.33*		76.78*		68.55*	

**Significant at 5%; Number of observations=50.*

levels of efficiency among female-headed households could stem from gender inequities in the rural areas in question, where women have more difficult access to land, capital and/or other financial services

CONCLUSION

The main hypothesis of this study is that season, farm size and modern technology adoption influence the efficiency of smallholder farms in the dry lands of Kenya. Efficiency is also hypothesized to be a function of several farm-specific factors for which data were available. The analysis of efficiency based on a comparison between ‘modern’ and ‘traditional’ technology adoption as well as ‘large’ and ‘small’ farmers tends to support Schultz’s “efficient but poor” hypothesis. Even though Schultz has been criticized for using scant empirical evidence to support his arguments (Ball and Pounder, 1996; Shapiro, 1983), his ideas are still relevant.

It has been demonstrated that there are overall inefficiencies in the way farmers use their resources. The culture of livestock keeping alongside arable agriculture has been continued in this lowland area regardless of unreliable rainfall. Since settlements in the study area are recent, it may be that farmers do not understand their environment well. The low percentage of full-efficient farmers thus tends to suggest that inefficiency is being driven by farmers trying to impose the culture of cultivation on unsuitable land. The farmers are trying to cope with the new harsh environment in which they try to experiment with their old culture of mixed farming. This suggests that they will need a generation of experience with their ‘new resource’—land—to ‘discover’ how to use it optimally. This idea is similar to Schultz’s emphasis on the value of farmers’ knowledge of their own resources and technology. Schultz observed that farmers are “on the look out for new and better seeds, fertilizer, ways of planting as well as the age-long techniques that have been refined and sharpened by countless years of experience” (P.45).

In interpreting the results of efficiency, the question of tastes and preferences in foods consumed and crops grown comes to mind. The preferred food in the study area is maize. Farmers persistently grow this crop and yet the crop performs poorly so often. Continued cultivation of maize in such circumstances also raises the question of farmers not having faith in markets. They reckon that they may be more assured of some food if they produced their own; because they may not be able to raise enough money to purchase food and because the food may not be available when needed (implying the fear of the prospect of market failure). The question of risk and uncertainty is important as well and may be having a role to play in influencing the efficiency of farmers. This suggests that there may be 'inefficiency by choice' rather than 'inefficiency by ignorance', and that assuring farmers of income by improving their livelihood opportunities and reducing perceived risk could improve 'efficiency'. However, this raises the unresolved problems related to the interpretation of efficiency.

The Tobit regression analysis indicates that efficiency is influenced by the age, gender and level of education of the farmer, alongside diversification and infrastructural development. It shows that human capital is key to improved technical efficiency. This supports the arguments by Solis et al. (2009) that investments in human capital provide the greatest returns in terms of socio-economic development. Thus, agricultural development in the rural areas of SSA should strengthen efforts to increase the level of knowledge among smallholder farmers.

According to the findings, diversifying the sources of household incomes is an effective way to enhance production through improved agricultural conditions. This result also suggests that off-farm work can contribute to farm productivity. The analysis also reveals that scale efficiency is positively influenced by land size, suggesting that land fragmentation negatively affects efficiency at the scale level. Thus, policies that aim at improving land management by discouraging land fragmentation are likely to increase production. The result showing that female-headed households are more efficient than male-headed ones suggests that policies aimed at improving farm production should address issues that limit women's ability to realize their full potential in farming activities rather than focusing on men alone. This in turn is expected to ensure improved household food security.

Finally, these findings are useful in designing poverty alleviation strategies in rural dry land areas in developing countries. It is often argued that one of the most important factors in developing agriculture is poverty, which leads to the overuse of natural resources such as land, in turn causing degradation and a decline in agricultural productivity. The evidence from this study indicates that policies directed at supporting rural infrastructure to facilitate market access can improve agricultural efficiency.

ENDNOTES

[1] The zero values for minimum capital suggest that some households neither used nor hired an ox-plough or tractor; they used simple tools like hoes whose use-value was as good as zero. Capital stock was not used because the data would have been highly skewed since only a few farmers owned tractors and ox-ploughs.

[2] In a household farming system, live animal sales may and are frequently not as a result of 'net' production (or biological off-take). They may actually be sales of part of the family capital, triggered by food shortages.

[3] With, say, three factors, a minimum of nine parameter estimates would be required in a translog model. In cases where there might be problems of insufficient data, this would be a serious disadvantage.

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