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Analysis of farm household technical efficiency in Northern Ghana using bootstrap DEA

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Luke N. Abatania[1], Atakelty Hailu[2] and Amin W. Mugera[3]

[1] PhD candidate, School of Agricultural and Resource Economics, The University of Western Australia
[2] Associate professor, School of Agricultural and Resource Economics, The University of Western Australia
[3] Assistant professor, School of Agricultural and Resource Economics, The University of Western Australia

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Abstract

Crop production is the main source of livelihood for households in Northern Ghana. The government is committed to improving crop production and knowledge about the technical efficiency of crop farms is essential in guiding policy decisions. This paper examined the technical efficiency of 189 crop farms in Northern Ghana using data envelopment analysis (DEA) with bootstrapping. We found that bias-corrected average technical efficiency of the sample farms is 77.26%. The estimated scale efficiency is 94.21%. In a second stage regression, we found that hired labour, geographical location of farms, gender and age of head of household significantly affect technical efficiency. Policy implications of the results are discussed.

Keywords: Technical efficiency, DEA, bootstrap, Ghana, OLS regression.

1. Introduction

The economy of Ghana is predominantly agrarian and agriculture is the largest sector. Agriculture accounts for more than 40 percent of Ghana's Gross Domestic Product (GDP) and employs over 60% of the workforce (Asuming-Brempong *et al.*, 2003). Smallholder farm households, mainly on a subsistence basis, carry out most of the agricultural production. Smallholders constitute 90 to 95% of the farming population and produce 80% of the agricultural annual output (Asuming-Brempong *et al.*, 2004). Smallholders are usually defined as those with land holdings of 10 ha or less. The average land holding for smallholders in the country is about 2 ha (Chamberlin, 2008).

Crop farming is the main preoccupation of farm households although it is not uncommon to find livestock enterprises in conjunction with crop farming. Crop farming is done under rainfed conditions using scarce resources (land, family labour and any cash the family is able to mobilise). Efficient use of scarce resources in fostering agricultural production has long been recognized and has motivated considerable research into the extent and sources of efficiency differentials in peasant farming (Alene *et al.*, 2006). A few studies have tried to address the issue of agricultural efficiency in Ghana (See for example, Al-hassan (2008a), Langyintuo *et al.* (2005), Abdulai and Huffman (2000)). These studies have focused on rice which is mono-cropped. In practice, farmers produce multiple crops in intercrop situations and efficiency analysis should consider all crop enterprises because of the synergies that exist among these enterprises as well as their competition for available farm household resources. Besides, there are jointness in production and a problem exists in separating the contribution of different inputs to different cropping enterprises (Chevas *et al.*, 2005). The appropriate analysis of productive efficiency should consider all crop outputs and production inputs in a multi-input, multi-output framework for each farm family. Fortunately, the framework for this type of analysis already exists. This paper addresses the problem of lack of appropriate analysis of production efficiency in Ghanaian agriculture. The present analysis is important given the contribution of agriculture in the national economy and the emphasis placed on increasing agricultural productivity (Government of Ghana, 2006).

The purpose of this study is to investigate the level and sources of technical efficiency differentials among farms in Northern Ghana. This is achieved by estimating the technical and scale efficiency of smallholder farms and establishing the factors that influence both technical and scale efficiency. The Northern area comprises of three regions out of ten administrative regions in the country. The area is the granary of the country in view of its contribution to the annual volume of staple grains. Technical efficiency is estimated in a multi-input and multi-output data envelopment analysis (DEA) framework. To the best of our knowledge, no study has considered the full complement of crops produced by farmers in estimating the technical efficiency of crop production in Ghana. This study contributes to the literature on the policy debate as to whether technical inefficiency is one of the major causes of low productivity in agriculture. By considering all major crops produced by the household, the analysis provides information relevant for informed policy decisions in relation to agricultural development. It also provides some understanding of the factors affecting technical efficiency in crop production. Importantly, policy recommendations are made from the findings of the paper to help increase technical efficiency of crop farmers.

The paper is organised into 6 sections. Section 2 examines the literature on the measurement of technical efficiency. It provides a background to the policy environment of agriculture in Ghana and gives the results of some empirical technical efficiency studies. In section 3, empirical models used in the paper are discussed. Section 4 discusses source of the data, relevant variables and summary statistics of variables used in the models. The empirical results are presented and discussed in Section 5. The conclusions and policy implications are presented in section 6.

2. Literature review

2.1 Policy environment of crop production in Ghana

The government of Ghana recognises the contribution that agriculture makes to economic development and has embarked on policies to strengthen the sector to enable it increase its output through productivity increase. There have been major policy shifts between capitalist and socialist policies in Ghana. At independence (in 1957), capitalist development policies that existed were replaced by socialist development policies (Miracle, 1970). The socialist approach to development was abandoned in 1966, following the overthrow of the ruling government and the economy shifted towards a market-oriented approach. The government introduced large subsidies on the cost of imported agricultural inputs and services in order to encourage farm mechanisation. The supply of purchased inputs was increased considerably in the period after 1966, mainly in pursuit of two major campaigns to promote farm production (Akoto, 1987). The first campaign was rto increase rice production to meet rising demand for the crop by urban consumers. The second campaign focused on raising farm output by direct appeals to smallholder farmers to expand the area under cultivation and by supporting the establishment of large-scale mechanised holdings. Through these campaigns, Ghana achieved self-sufficiency in rice production between 1974 and 1975 (Killick, 1978).

A major feature of agricultural development policy in Ghana in the early 1970s was the formation of single product development boards for commodities such as cotton, bast fibres, grains, cattle and meat (Nyanteng and Seini, 2000). Policy makers believed that the establishment of development boards to offer advice and incentives and to oversee the production of specific crops could successfully exploit the potential of smallholder farmers. Agricultural policies were supported by a massive rural development scheme designed to provide the basic infrastructure of roads, water and electricity that would encourage people to stay in the rural areas where agricultural land is available. The period preceding 1976 held some hope for agricultural development in Ghana. On the whole, there was a positive response to the policies that emphasized private sector development of agriculture as well as the policies that encouraged self-sufficiency in food and industrial raw material production (Seini, 2002). However, the period 1976 to 1982 was one of despair. The macroeconomic and political environments were unfavourable for agricultural development. Inflation rose from a 3.5% in 1970 to 41% in 1976 and reached 121.2% in 1977 due to government expansion of money supply to finance budget deficits (Nyanteng and Seini, ibid).

In the middle of 1980s, the economy of Ghana underwent structural changes; overall trade was liberalised, farm subsidies removed and agricultural input and output markets privatised. The structural changes were necessitated by a decline in economic growth (Jebuni and Seini 1992). Following structural adjustment policies during 1984-90, Ghana's economy and society have recovered, in important senses, from years of deep recession, hyperinflation, and disinvestment. Ghana has had an average real growth in GDP of 5.7% per annum during 1984-89 (Jon, 1991). Although the structural adjustment policies brought about improvements at the macro level, at the micro level there was unequal socioeconomic and spatial development in the country (Konadu-Agyemang, 2000) and increasing rural poverty became a reality. The government embarked on policies to reduce poverty to consolidate the gains of the structural adjustment programs. The government implemented the first Ghana Poverty Reduction Strategy (GPRS I) from 2003 – 2006 to address the economic decline. The policy thrust of the macroeconomic framework under GPRS I was towards promoting macroeconomic stability for sustainable economic growth and poverty reduction. Some progress was made in the agricultural sector. Farmers' access to mechanized tillage increased from 5% in 2002 to 12% in 2004 as against a target of 15%, while access to processing equipment increased from 24% in 2003 to 42% in 2004. Cereal post harvest losses achieved its intended target of 15-20% (Government of Ghana, 2006).

In spite of the progress made in agriculture, the stagnation of technologies and in some areas, the wide gender inequalities in access to and control over land and agricultural inputs, including extension services, as well as adverse environmental factors such as climate variability and land/soil degradation, continue to be challenges posed to the growth potential of the sector. In the Second Growth and Poverty reduction Strategy (GPRS II) the government placed emphasis on increasing agricultural productivity, among other things (Government of Ghana, 2006). Policy decisions of this sort need to be informed by the efficiency with which farm households use the resources available as well as the factors that affect this efficiency. The problem about Ghanaian agriculture that needs to be addressed is that very little is known about the efficiency with which farmers produce. Related to this knowledge gap, one may pose the question: given the resources available to farmers, are Ghanaian farmers producing the maximum possible output that they could produce? In other words, are Ghanaian farmers technically efficient? This question can be answered by using the nonparametric DEA approach to empirically examine the technical efficiency of farms in Ghana.

2.2 Empirical work on technical efficiency in developing countries

DEA has been applied in empirical efficiency studies in Smallholder agriculture in developing countries of which Ghana is one. Coelli et al (2002) used the DEA framework to study the technical, allocative and scale efficiency of rice cultivation in Bangladesh. They estimated the mean technical, allocative, cost and scale efficiency for dry season rice production to be 0.694, 0.813, 0.562 and 0.949. Efficiency estimates for wet season rice were similar but a few point lower than dry season estimates. They attributed allocative inefficiency to over use of labour and fertiliser and concluded that large families are likely to be more inefficient, that farmers who have better access to input markets and those who do less farm work tend to be more efficient. Rios and Shively (2005) investigated farm size and efficiency measures for coffee in Vietnam using a two-stage DEA approach and found that on the average larger farms are more technically and cost efficient than smaller farms. The mean technical and cost efficiency for large farms were 0.89 and 0.58. The corresponding values for small farms were 0.82 and 0.42. They found that the length of irrigation pipe and higher education reduce efficiency on small farms. Alene, Manyong et al (2006) estimated the production efficiency of intercropping annual and perennial crops in Southern Ethiopia using SFA, DEA and parametric distance functions (PDF) approaches. Mean technical efficiency for SFA was lower than the mean technical efficiency of DEA and PDF. They conclude from their findings that farmers in Southern Ethiopia are efficient in the use of land and other resources through innovative cropping systems. They noted that technologies that are appropriate to such systems may be needed for greater intensification. Thiam, Bravo-Ureta et al (2001) has presented a comprehensive review of the literature on developing country agriculture and Bravo-Ureta, Solis et al (2007) has carried out a meta regression analysis of technical efficiency in farming. Both papers have examined the application of the DEA framework in developing country agriculture among other methods. To the best of our knowledge, the literature on DEA application in Ghana does not include agriculture. There are a number of published papers in the health sector (Osei, d'Almeida et al (2005), Akazili, Adjuik et al (2008)) that have used DEA methods.

Given the advantages and disadvantages of the methods for estimating technical efficiency, there is no clear advantage of using one method over the other (Resti, 2000). It has been suggested that the decision to use one method over the other depends on the objective of the study, data available and the researcher’s personal preference (Wadud and White, 2000).

There is, however, evidence from empirical studies to suggest that the choice of a method of estimation can impact the estimated technical efficiency (Bravo-Ureta *et al.*, 2007). In general estimated mean technical efficiency from stochastic frontier models are lower than the mean technical efficiency estimated from non-parametric deterministic models as reported by Alene, Manyong et al (2006) and Bravo-Ureta, Solis et al (2007). Moreover, when we do not have any knowledge on the data generating process, nonparametric methods are more suitable for estimating technical efficiency. We shall return to this later.

3. Methodology

3.1 Production technology and technical efficiency

The estimation of technical efficiency begins with a description of the structure of production technology. The description starts with definitions of feasible sets for inputs and outputs (technology set). The boundaries of these sets then define efficient production activities. The structure of production technology is described in terms of distance functions. Details of input and output distance functions can be found in Färe and Primont (1995), Kumbhakar and Lovell (2000), Coelli, Prasada et al (2005). For the purpose of this paper technology set (T) is defined by,

$$T = \{(x, y) : x \in R_+^N, y \in R_+^M, x \; can \; produce \; y\}, \quad (1)$$

where x denotes an N x K input matrix of non-negative real numbers and y denotes a non-negative N x M output matrix. The technology set can also be defined in terms of output sets and input sets. We provide details of the input requirement set below, as our analysis uses the input-orientation. The input requirement set is defined as,

$$L(y) = \{x : x \; can \; produce \; y\} = \{x : (x, y) \in T\} \quad (2)$$

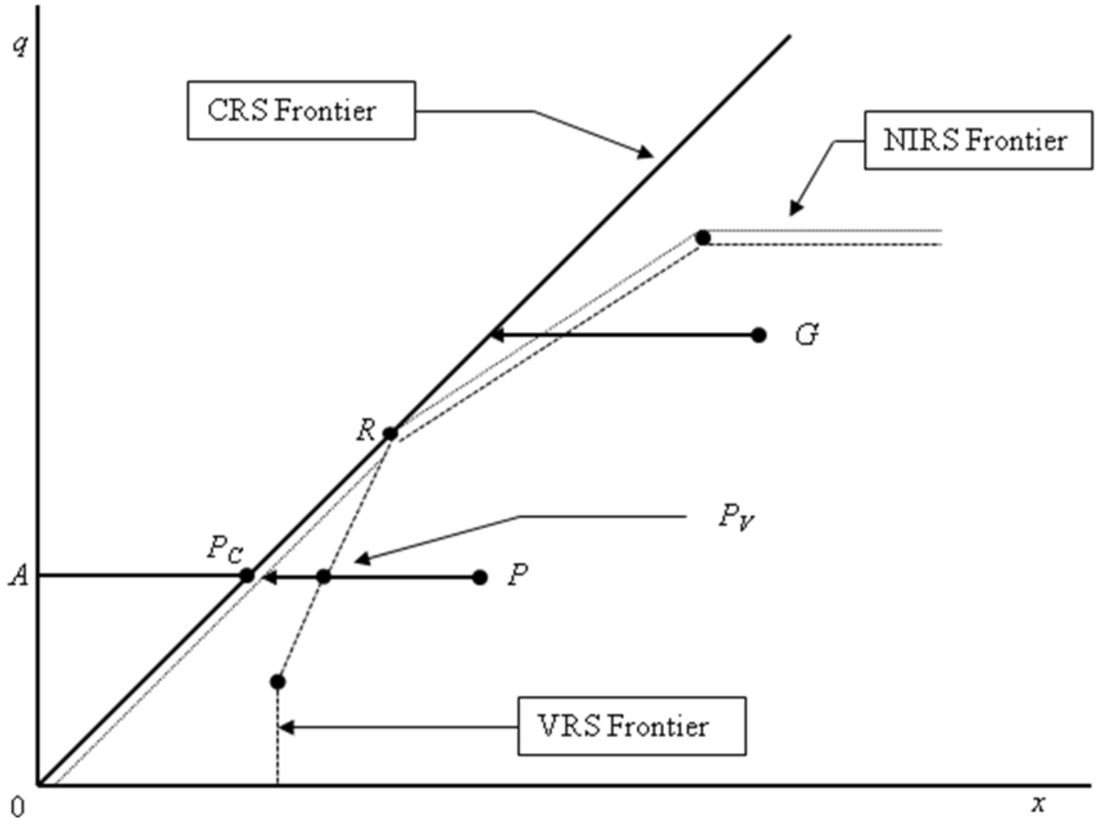
where $L(y)$ is the input set, which consists of all input vectors, x, which can produce a given output vector y.

The output and input sets define production possibility frontiers against which the technical efficiency performance of production activities can be measured. Any production activity that is on the frontier is technically efficient while activities off the frontier are inefficient. Thus, the distance of a production activity from the frontier is a measure of efficiency. On this basis, output-oriented, input-oriented or directional distance functions can be defined. In this paper we focus on the input-oriented distance function. We use the input orientation because farmers in the study area have control over their inputs use and little or no control over the output they produce. The input-oriented distance function is defined as follows:

$$D_I(y,x) = \max\{\lambda : x/\lambda \in L(y)\} \tag{3}$$

where λ is the distance from a producer to the boundary of production possibilities. An input distance function adopts an input-conserving approach to the measurement of the distance from a producer to the boundary of production possibilities. It gives the maximum amount by which a producer's input vector can be radially contracted and still remain feasible for the output vector it produces (Kumbhakar and Lovell, 2000). The distance function defined above is illustrated in figure 1.

Figure 1: Efficiency measures



Source: Coelli, Prasada et al (2005)

Figure 1 above illustrates a single input-single output technology. Constant Returns to Scale (CRS) and Variable returns to Scale (VRS) as well as Non-increasing Returns to Scale (NIRS) DEA frontiers are indicated in the figure. Under CRS, the input-oriented technical inefficiency of point P is the distance PPc; under VRS, the technical inefficiency of this point is only PPv. The difference between the two measures is due to scale inefficiency. These concepts can also be expressed in terms of ratio efficiency measures as:

$$TE_{CRS} = APc/AP$$

$$TE_{VRS} = APv/AP$$

$$SE = APc/APv$$

where TE_{CRS} is technical efficiency score under CRS, TE_{VRS} is technical efficiency score under VRS and SE is scale efficiency. The nature of returns to scale for a particular farm can also be determined by comparing the technical efficiency score under NIRS (TE_{NIRS}) with the TE_{VRS} score for that farm. If the two scores are equal as in the case of farm G in Figure 1, then decreasing returns to scale apply; if the two scores are unequal as is the case for farm P, then increasing returns to scale exists for that farm.

3.2 Empirical DEA model

Given that there is an underlying production technology, technical as well as scale efficiencies can be estimated empirically. For a sample of *n* observations of farm households using *k* inputs to produce *m* outputs the input and output vectors for the *i*th household can be represented as (X_{ki}) and (Y_{mi}) respectively. For a household using (X_{ki}) to produce (Y_{mi}), the input-oriented technical efficiency estimate is defined by:

$$\text{TE}\,(X_{ki}, Y_{mi}) = \underset{\theta, Z}{Min}\,\theta, (\theta, X_{ki}, Y_{mi})$$

$$\text{Subject to:} \left\{ \begin{array}{l} y_{mi} \leq \sum_{i=1}^{I} Z_i y_{mi}, m = 1, 2, ...M, \\ \sum_{i=1}^{I} z_i x_{ki} \leq \theta x_{ki}, k = 1, 2, ...K, \\ z_i \geq 0, i = 1, 2, ...I, \end{array} \right\} \tag{4}$$

where θ_i = technical efficiency estimate to be calculated for each farm household$_i$, y_{mi} = quantity of output *m* produced by farm household$_i$, x_{ki} = quantity of input *k* used by farm household$_i$ z_i = intensity variable for household *i*. A household is considered to be technically efficient if $\theta = 1$, while a household with $\theta < 1$ is considered to be technically inefficient. The model above assumes constant returns to scale (CRS), which holds that all firms (farm households) operate at the optimum scale (Mugera and Featherstone, 2008). However, because of imperfections in agricultural markets (input/output markets) farms seldom operate under CRS. Therefore, adding equation (6) in the constraints imposes variable returns to scale (VRS), and equation (7) non-increasing returns to scale (NIRS):

$$\sum_{i=1}^{I} Z_i = 1 \tag{5}$$

$$\sum_{i=1}^{I} Z_i < 1 \tag{6}$$

3.3 Bootstrapping DEA efficiency estimates

DEA as an approach to the measurement of technical efficiency is best suited for multi-output technologies in a practical sense (Gocht and Balcombe, 2006). Even though stochastic frontier multiple output "distance functions" have been estimated in the literature (Morrison Paul *et al.*, 2000), the choice and use of appropriate instruments to deal with problems of endogeneity has not been sufficiently addressed. DEA also seems to be more appropriate when the knowledge about the underlying technology is weak (Kalirajan and Shand, 1999). A major criticism of the DEA approach is that it produces point estimates of efficiency that are biased and lack statistical properties. Bootstrapping methods have been developed for estimating the bias and correcting the efficiency estimates. Bootstrapping is a method of testing the reliability of a data set by creating a pseudo-replicate data set. Bootstrapping allows you to assess whether the distribution has been influenced by stochastic effects and can be used to build confidence intervals for point estimates, which normally cannot be derived analytically. Random samples are obtained by sampling with replacement from the original data set, which provides an estimator of the parameter of interest (Gocht and Balcombe, 2006). For details of the bootstrap procedure the reader should refer to Simar and Wilson(1998), Simar and Wilson (2000).

3.4 Scale efficiency analysis

Scale efficiency (SE) for each household is estimated and decomposed as follows:

if

$$\frac{TE_{CRTS}}{TE_{VRTS}} < 1 and \frac{TE_{CRTS}}{TE_{NIRTS}} = 1, \tag{10}$$

then there are increasing returns to scale (IRTS); if

$$\frac{TE_{CRTS}}{TE_{VRTS}} < 1 and \frac{TE_{CRTS}}{TE_{NIRTS}} < 1, \tag{11}$$

then there are decreasing returns to scale (DRTS); and if

$$TE_{CRTS} = TE_{VRTS} = TE_{NIRTS}, \tag{12}$$

this is the most productive scale size (MPSS).

There are two groups of farms that constitute the MPSS, those that are both technically and scale efficient and those that are technically inefficient but scale efficient (Mugera and Langemeier, 2011). For analytical purposes, the former group is considered to be operating under constant returns to scale (CRTS), i.e.:

$$TE_{CRTS} = TE_{VRTS} = TE_{NIRTS} = 1 \tag{13}$$

and the latter group is considered to operate under MPSS, i.e.:

$$TE_{CRTS} = TE_{VRTS} = TE_{NIRTS} < 1 \tag{14}$$

The DEA model was solved using the computer software FEAR (Wilson 2009) to obtain the technical efficiency estimates.

Studies examining the factors influencing technical efficiency typically adopt a two step approach (Helfand and Levine (2004); Haji (2007)). We adopt the same approach in this paper. In the first step, we estimated technical efficiency of crop farm households in Northern Ghana using DEA with bootstrapping. In the second step, we used an ordinary least squares (OLS) regression model to regress the bias-corrected technical efficiency estimates under

VRTS against factors that are assumed to affect technical efficiency. As a rule of thumb it is recommended that the original technical efficiency estimates should not be corrected for bias unless the absolute value of the estimated bias is greater than a quarter of the estimated standard deviation of the parameter estimated (Efron and Tibshirani, 1993). Our choice of the bias-corrected technical efficiency estimates instead of the original technical efficiency estimates is motivated by an application of this rule of thumb in which the absolute value of the bias (0.2048) is greater than a quarter of the estimated standard deviation (0.0524). In practice, due to inherent bias of the DEA estimator, the bias-correction has almost always to be performed (Daraio and Simar, 2007). The Tobit model is commonly used to regress the technical efficiency estimates against factors that are thought to influence technical efficiency. This is applicable only if the efficiency estimates are not corrected for bias.

For mathematical details of the model, the reader should refer to Tobin (1958). We use the log-likelihood to explain why this model is inappropriate when the efficiency estimates have been corrected for bias. The log-likelihood for the Tobit model is given as:

$$\ln L = \sum_{\theta_i > 0} -\frac{1}{2}\left[\log(2\pi) + \ln\sigma^2 + \frac{(\theta_i - Z_i^{'}\beta)}{\sigma^2}\right] + \sum_{\theta_i = 0} \ln\left[1 - \Phi\left(\frac{Z_i^{'}\beta}{\sigma}\right)\right] \tag{15}$$

where θ_i as defined in equation (4), Z_i is a vector of factors affecting technical efficiency, β is a vector of unknown parameters to be estimated, σ^2 is the variance of θ_i and Φ is the standard normal cumulative distribution function. From equation (15) there are two parts of the log-likelihood which correspond to the OLS regression for the nonlimit observations and the relevant probabilities for the limit observations, respectively (Greene, 2002). When the bias-corrected efficiency estimates are used in the Tobit model, the second part of equation (15) becomes zero and the model reduces to an OLS regression model. The OLS regression model used in the analysis is as follows:

$$TE = \beta_0 + \beta_1 nage + \beta_2 nagesq + \beta_3 gender + \beta_4 educ$$
$$+ \beta_5 nfert\cos t + \beta_6 nhiredlab + \beta_7 nr + \beta_8 uwr + \varepsilon$$

where *TE* = estimated bias-corrected technical efficiency index, *nage* = age of head of household normalised by its mean, *nagesq* = age of head of household squared and normalised by its mean, *gender* is a dummy variable (male = 1, female = 0), *educ* =dummy variable for educational status of head of household (1= formal education, 0 = otherwise), *nfertcost* = cost of fertiliser input used normalised by its mean, *nhiredlab* = cost of hired lab used normalised by its mean, *nr* = northern region, *uwr* = upper west region, β_i = unknown parameters to be estimated and ε in an error term.

The age of the head of household is an important factor that influences technical efficiency. The head of household takes production management decisions on behalf of the household. It is expected that older heads would have more experience and would be more efficient in crop production than younger heads. On this basis, age is expected to have a positive influence on technical efficiency. However it is often presumed that younger farmers with a longer planning horizon and who are willing to take risk are more likely to try innovations (Polson and Spencer, 1991). These innovations are likely to make younger farmers more technically efficient than older farmers. In such a situation age would have a negative effect on technical efficiency. Gender refers to the sex of the head of household. In Ghana, males and females have differential access to agricultural services in favour of males. Besides, heads of household are normally males and a female becomes head of household in the absence of a surviving male who is old enough to be head of household. Given this situation, females are likely to have fewer years of experience as heads of household compared to males. On this basis, it is expected that farms households headed by males would be more technically efficient compared to those headed by females. The level of education of the head of household can influence technical efficiency. Educated heads of household are able to read and interpret extension messages among other information. Therefore, the educational status of the head of household is an important factor to consider in examining the factors affecting technical efficiency. Education is expected to have a positive influence on technical efficiency. The use of fertilisers enhances crop yields. Households that use fertilisers are expected to obtain higher yields for any given set of production inputs used compared to households that do not use fertilisers. The use of fertilisers is thus an important factor to consider in the study of factors affecting technical efficiency. The use of fertilisers is expected to have a positive influence on technical efficiency. Similar to the use of fertilisers, the use of hired labour for farm operations enhances crop yields and is expected to have a positive influence on technical efficiency. The geographical location of farms is an important factor to consider in the analysis of factors affecting technical efficiency. Socioeconomic as well as climatic conditions vary across geographical locations. It is expected that locations that have favourable conditions for crop production would have a positive influence on technical efficiency. The literature on factors affecting technical efficiency with particular reference to Sub-Saharan Africa provides mixed results.

We reviewed 19 recent studies (2002 -2011) and found mixed results for the factors most frequently included in technical efficiency models: age, gender, education, farming experience, household size, extension, credit, farm size, and membership of farmers' group. This suggests that there is need for further studies to contribute to the debate on factors affecting technical efficiency in African agriculture. Table 1 provides a summary of the studies reviewed in terms of approach to the estimation of technical efficiency and the relationship between technical efficiency and the factors listed above. The symbols under each factor describes its relationship with technical efficiency as follows:

"+" there is a positive relationship between technical efficiency and the factor,

“-” there is a negative relationship between technical efficiency and the factor,

“+*” there is a significant positive relationship between technical efficiency and the factor

“-*” there is a significant negative relationship between technical efficiency and the factor.

Table 1: Consistency of findings of factors affecting technical efficiency

		Relationship between technical efficiency and factors affecting technical efficiency								
Study	Approach	Age	gender	education	experience	household size	Extension	Credit	Membership of group	Farm size
Ogunniyi and Oladejo (2011)	DEA		+*	-*	-*	+*				
Amadou (2007)	SFA	+		-*	+	+	-	-*	+	
Chirwa (2007)	SFA			+			+		-*	
Kyei et al. (2011)	SFA	-		+	+	+	-	-		
Al-hassan (2008b)	SFA	+*	-	+*		+*	+*	-		
Haji (2007)	DEA	+		+		-*	-*	-		-*
Dzene Richman (2010)	SFA	+*	+*	+*		-*				
Wouterse (2010)	DEA	+*		-						
Binam, Tonyè et al. (2004)	SFA	+		+,-*			+	-*	-*	
Binam, Sylla et al. (2003)	DEA	+*		+,-				+	-*	-*
Sherlund, Barrett et al. (2002)	DEA/SFA	+		+	-					
Speelman et al. (2008)	DEA	+,-	-	-,+		-				
Chavas, Petrie et al. (2005)	DEA		+							-*
Ogundari and Ajibefun. (2004)	SFA			+			-			
Ajibefun, Daramola et al. (2006)	SFA			+	+					+
Ogundele. (2006)	SFA	+		-*	+*	-	-			+*
Kibaara. (2005)	SFA	+	+	-*						
Okike et al. (2004)	SFA	-*						-*	+*	
Onumah et al. (2010)	SFA	-*	+*	-*	-*					

4. Data and variables in empirical models

The data used in this study comes from the fifth round of the Ghana Living Standards Survey (GLSS5). GLSS5 is a nationally representative multipurpose household survey which was conducted in 2005-2006. A total of 580 enumeration areas (EA) were randomly selected from enumeration areas defined from the 2000 population and housing census. A sample of 15 households was selected from each EA bringing the total sample to 8700 households. The total sample included 1904 households from Northern Ghana, the area of focus for this study. Northern Ghana comprises 3 (Northern region, Upper East region, Upper West region) out 10 administrative regions in the country.

In selecting a subsample for our analysis, we took into account households that provided consistent information on inputs and outputs relevant for our analysis. A total of 521 households were included in the subsample at this stage. We then considered households that grow staple grain crops (maize, sorghum, millet, rice, cowpea, and groundnut) for inclusion in the analysis. To check the data for consistency, we used scatter plots of inputs against output and eliminated outlier farms. We also eliminated cases with missing data for any of the variables included in the models. We then estimated initial DEA models under CRST, VRST and NIRST assumptions (with and without bias correction) and plotted these against each other to further reveal outlier farms. We came up with a sample of 189 farms for the analysis reported in this paper. Table 2 gives the definition and summary statistics of the variables used in the models.

The empirical DEA models contain 3 inputs and 6 outputs. The inputs are: land measured as the total cultivated area in hectares; household labour measured as the number of household members available to work on the household farm and calculated as man equivalents of labour per household; and intermediate inputs measured as the cost of intermediate inputs used in production and calculated in US dollars (¢9150 = US$1) at market prices. The outputs are the grains measured in kilograms per household. Six grain crops are considered in the analysis; maize, sorghum, millet, rice, beans and groundnuts.

Table 2: Descriptive statistics of variables

Variable	Definition	Minimum	Maximum	Mean	St. Dev.
Production inputs per household					
cultarea	Cultivated land area in hectares	0.4	7.6	1.45	1.05
hhalab	Household labour in man equivalents	0.5	16.8	3.56	2.25
varcost	Variable input cost calculated at market prices	1.25	388.69	56.57	64.04
Crop outputs					
mz (n=136)	maize grain (kg)	0.00	5500.00	324.74	631.89
sg (n=97)	sorghum grain (kg)	0.00	2289.00	144.67	256.75
mlt (n=137)	millet grain (kg)	0.00	1860.00	171.72	208.28
rc (n=93)	rice grain (kg)	0.00	2200.00	132.38	275.59
cp (n=93)	cowpea grain (kg)	0.00	471.43	57.63	92.04
gn (n=156)	groundnut grain (kg)	0.00	1804.00	272.47	342.29
Factors affecting technical efficiency					
age	Age (years) of head of household	19	78	46.7	14.56
fertcost	Cost of fertilisers (US$)	0	318.23	15.86	37.14
hiredlab	Cost of hired labour (US$)	0	132.6	9.82	21.99
Frequency distribution of dummy variables					frequency
gender	Gender of head of household	0=female			21
		1=male			168
educ	Educational status of head of household	0=illiterate			133
		1=educated			56
nr	Farms located in the northern region				43
uer	Farms located in the Upper east region				129
uwr	Farms located in the Upper West region				17

5. Empirical results

5.1 DEA technical efficiency estimates

The standard DEA technical efficiency estimates under CRTS, VRTS and NIRTS are shown in Table 2. The results indicate that the majority of farms are technically inefficient under VRTS, the basis of our discussion of the results as earlier indicated. The average technical efficiency under VRTS is 85.90% with a range from 50.14% to 100.00%. .The results in Table 2 show that 81 farms (42.86% of the sample) are technically efficient under VRTS while 65 (34.39% of sample) and 56 (29.63% of sample) are technically efficient under CRTS and NIRTS respectively.

Table 2: Frequency distribution of technical/scale efficiency of farms in Northern Ghana

	Frequency (number of households under different efficiency measures			
Technical/Scale Efficiency	VRTS	NIRTS	CRTS	SE
0.0 0- 0.25	0	0	0	0
0.25 - 0.50	0	3	4	0
0.50 - 0.75	56	62	68	8
0.75 -0.99	52	59	61	124
1.00	81	65	56	57
Total	189	189	189	189
Summary statistics of technical/scale efficiency				
Minimum	0.5014	0.4882	0.4882	0.5509
Maximum	1.0000	1.0000	1.0000	1.0000
Mean	0.859	0.8223	0.8092	0.9421
Standard deviation	0.1532	0.1655	0.1651	0.0856

When the efficiency scores are corrected for bias, no farm is technically efficient. As stated earlier. The frequency distribution of the bias-corrected technical efficiency estimates are shown in Table 3 together with quartiles of the 95% confidence interval. The average bias-corrected DEA technical efficiency score is 77.26% and 76 farms out of the sample of 189 farms operate with technical efficiency below the sample average technical efficiency. The average technical efficiency compares well with the findings of previous studies. Binam et al (2004) estimated mean technical efficiencies of 0.73, 0.75 and 0.77 for three different cropping systems (mono-cropped maize, mono-cropped groundnut and maize-groundnut intercrop) in Cameroon. Similarly, Piesse et al (1996) estimated mean technical efficiencies of 0.67, 0.70 and 0.79 for smallholder agriculture in three regions (KaNgwane, Lebowa and Venda) of South Africa.

Table 3: Distribution of Bias-corrected Technical Efficiency (VRTS) of farms in Northern Ghana

Technical Efficiency	Number of households	Percentage of sample
0.0 0- 0.25	0	0
0.25 - 0.50	3	2
0.50 - 0.75	70	37
0.75 -1.00	116	61
Total	189	100
Summary statistics of bias-corrected technical efficiency		
Minimum		0.4671
Maximum		0.9281
Mean		0.7726
Standard deviation		0.1238
Quartiles of 95% confidence interval		
	Lower bound	Upper bound
First quartile	0.5571	0.7245
Median	0.6212	0.9136
Third quartile	0.6949	0.9946
Mean	0.6252	0.8544

The distributions of DEA technical efficiency estimates under CRST, VRTS and NIRST illustrated by their kernel densities are shown in Figure 2. The VRTS density curve lies to right of CRST and NIRST density cures, implying that crop farms in Northern Ghana operate closer to the technology frontier under VRST compared operating under CRTS or NIRST. In general, farms operating under NIRST are closer to the technology frontier at lower levels of technical efficiency but are further away from the frontier at higher levels of technical efficiency when compared to farms operating under CRST.

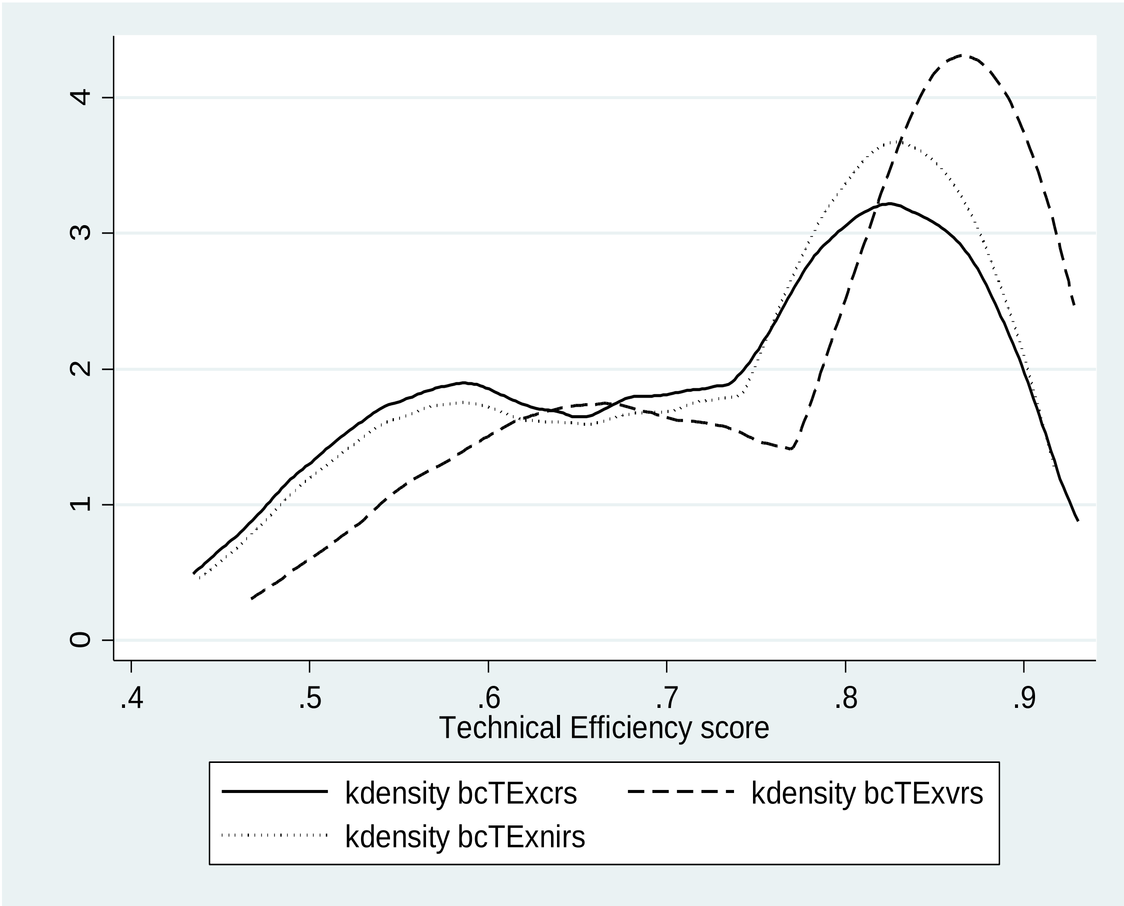


Figure 3: Distribution of bias-corrected DEA technical efficiency of farms in Northern Ghana

5.2 Scale Efficiency Analysis

An analysis of the scale of operation of the sample farms revealed that most of the sample farm households are not scale efficient. Only 57 farms (representing 30.16% of the sample) are scale efficient. The estimated scale efficiency ranged from 55.09% to 100% with an average scale efficiency of 94.21% and 59 farms (31.22% of the sample) operate below the average. The average scale efficiency and the number of farms operating above the average suggest scale efficiency is high and that technical inefficiency is attributable to managerial incompetence. The frequency distribution and summary statistics of estimated scale efficiency are shown in Table 2 above.

A decomposition of the scale efficiency estimates on the basis of the nature of returns to scale (Table 4) indicates that 88 farms (46.56%) operate under increasing returns to scale while another 44 farms (23.28%) operate under decreasing returns to scale. Fifty-six (23.63%) of the farms operate under constant returns to scale while the remaining farm (0.53%) operates under the most productive scale size, being technically inefficient but scale efficient.

Table 4: Nature of returns to scale of farms in northern Ghana

Nature of returns to scale	Number of households	Percentage of sample
Increasing returns to scale	88	46.56
Decreasing returns to scale	44	23.28
Constant returns to scale	56	29.63
Most productive scale size	1	0.53
Total	189	100.00

We examined the characteristics of farms under various returns to scale with respect to input use. On the average farms operating under IRTS use less land and spend less on variable inputs but use more household labour compared to those operating under CRTS. CRTS is the desirable scale of operation for farms as it both technically and scale efficient.

On the other hand, farms operating under DRTS use more of land and household labour but spend less on variable inputs compared to those operating under CRTS. Farms that operate under MPSS on the average use more land but use less household labour and spend less on variable inputs compared to those CRTS. A summary of the characteristics of farms with respect to input use under different returns to scale is provided in Table 5.

Table 5: Characteristics of farms with respect to input use under different returns to scale

Input characteristics	Observations	Minimum	Maximum	Mean	St. Dev.
CRTS	56				
Cultivated area (ha)		0.4	7.6	1.88	1.54
Household labour		0.5	9.9	3.21	2.21
Variable input cost		1.25	354.16	68.47	73.68
IRTS	88				
Cultivated area (ha)		0.40	3.60	1.08	0.63
Household labour		0.70	8.60	3.27	1.49
Variable input cost		3.48	348.31	42.34	45.54
DRTS	44				
Cultivated area (ha)		0.80	13.20	2.14	1.93
Household labour		1.00	16.80	4.69	3.29
Variable input cost		11.91	384.44	67.05	75.43
MPSS	1				
Cultivated area (ha)		2.40	2.40	2.40	-
Household labour		2.80	2.80	2.80	-
Variable input cost		65.39	65.39	65.39	-

Given that a greater number of the sample households (108 representing 57.14%) are technically inefficient and a much greater number (132 representing 69.84%) are scale inefficient it would be necessary to make every effort to make the inefficient households become efficient in crop production. This effort is better informed by the factors that affect the technical efficiency, given that scale efficiency in the study area is relatively high. The factors are discussed in the next section.

5.3 Factors affecting technical and scale efficiency

Results of the OLS regression model of factors affecting technical efficiency (with the bias-corrected technical efficieincy as independent variable) are presented in table 7. Marginal effects of the independent variables are the same as the coefficient estimates reported in Table 7. The results indicate that age and gender of head of hosehold, hired labour and geogarphical location of farms significantly affect technical efficiency. The constant term is also significant in the model.

Table 7: OLS regression model output of factors affecting technical efficiency

Dependent variable = bias-corrected technical efficiency

Independent variables	Coefficient	Standard error
nage	-0.4229**	0.1819
nagesq	0.2198**	0.0953
gender	-0.0944***	0.0283
educ	-0.0195365	0.0198
nfertcost	0.0008662	0.0038
nhiredlab	0.0093**	0.0040
nr	0.0444**	0.0217
uwr	0.0357	0.0311
constant	1.0420***	0.0982

Age of head of household and the square of the age of head of household were found to be significant at the 5% level with a negative and a positive relationship to technical efficiency respectively. Given the quadratic term of age in the model, the marginal effect of age on technical efficiency (evaluated at the mean age) is 0.77. This implies that older heads of household are likely to be more technically efficient in crop production than households with younger heads of household. Heads of household take crop production management decisions on behalf of the household. It is conceivable that older heads of household would have more experience in crop production that could lead to more efficient production. The next significant factor affecting technical efficiency is the gender of the head of household. The results show that female heads of household are more technically efficient compared with their male counterparts. This observation runs contrary to a priori expectation. It may well be the case that female-headed households in the study sample benefit from special programs aimed at bridging the disparity between men and women in terms of access to agricultural inputs and services. Our data does not provide this evidence, however government policy advocates the need to bridge the gap between men and women in terms of access to production inputs and services (Government of Ghana, 2006). Such programs could enhance the productivity of female-headed hoiuseholds and make them more techncally efficienct than male-headed households. The use of hired labour was found to have a significant positive relationship with technical efficiency at the 5% level of significance. The implication is that households that use hired labour are more techncially efficient compared to those that do not use hired labour. This means that the techncial efficiency of farms in Northern Ghana could be increased if farmers having labour constraints could gain access to hired labour.

The geographicla location of farms influences the technical efficiency of farms in Northern Ghana. The results of the OLS gression model indicated that as one moves from the Upper East region to the Northern region and the Upper West region, technical efficiency increases. The increase in techncial efficiency between the Upper East and Northern region is significant at the 5% levell while the increase in technical efficiency between the Upper East and West regions is not statistically significant. The Upper East region has poorer soils and is dryer compared to the other regions. This could account for the observed differences. However, this paper does not have enough evidence to support this attribution and further invetigation is needed to explain the observed regional differences.

6. Conclusions and policy recommendations

This paper estimated the technical and scale efficiency of farm households engaged in crop production in Northern Ghana and established the factors affecting technical efficiency. We used DEA with bootstrapping to estimate the technical and scale efficiency and a OLS regression model to establish the factors affecting technical efficiency. The empirical results provide evidence that technical inefficiency in crop production exists among the sample farm households. The estimated average technical efficiency of 77.26% implies that, on average farm households could reduce their farm inputs by 22.74% and still produce the present level of output. The implication is that either there is a lack of utilisation of the best available technology by farm households or farm households do not have access to the best technology.

The OLS regression model analysis indicates that age and gender of head of hosehold, use of hired labour, and relative geographical location of farms significantly influence technical efficiency of crop production in Northern Ghana. Older farmers are more technically efficient compared to younger farmers. Male farmers are less technically efficient compared to their female counterparts and the use of hired labour increases techncial efficiency. These findidngs are consistent with the findings of previous studies on techncial efficiency in African agriculture (see Table 1). Finally, the OLS regression model anaysis indicates that farms located in the Upper East region are less techncially efficient comapared to farms in the Northern but are statistically equally efficienct as farms in the Upper West region.

The findings of this paper have important policy implications. There is indication from the techncial efficiency estimates that majority of the sampled farm households either do not have the best technology available or are not utilising the available technology. Any policy intervention directed at bridging this technology gap or lack of utilisation of exisiting technology would have the effect of increasing the overall technical efficiency of farms in Northern Ghana. Specific intervention policies need to be designed and targeted at spepcific types of farm households. Currently the government of Ghana provides agricultural extension services to farmers free of charge through the Department of Agriculture. However, as noted by Lado (1998), there is a relatively large shortfall in the number of extension personnel with the relevant skills and the willingness to work in rural areas where most of the crop production takes place. In general if agricultural productivity can be increased through an increase in techncial efficiency, resources can be freed from the agricultural sector for industrial sector growth in line with government industrialisation objectives.

Some adjustments in the scale of operation of farms would be required in an attempt to achieve efficiency in crop production. From the scale efficiency analysis, 88 farms need to increase the area under cultivation without the need to adjust the other inputs while another 44 farms need to reduce the amount of family labour input into crop production. The geographical location of farms accounts for differences in the scale of opreation of farms. However, the specific factors that are responsible for differences in scale are not known and were not examined in the present study. This issue can form a seprate study to understand the factors that account for variation in scale size so that appropriate strategies can be implemented to bring farms to the optimal scale of operation.

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