

Research Article

Analysis of Determinants of Productivity and Technical Efficiency among Smallholder Common Bean Farmers in Eastern Uganda

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Abstract: The study evaluated factors influencing bean productivity and technical efficiency among smallholder farmers in Eastern Uganda, using a stochastic frontier model and a Tobit model. Findings showed that bean productivity was significantly influenced by plot-size, seeds and planting fertilizer; mean technical efficiency for sampled farms was 48.2%. The Tobit model estimation revealed that technical efficiency was positively influenced by value of assets (at 1% level), extension service and group membership (at 5% level); while age and distance to the factor market negatively influenced technical efficiency at 10 and 5% levels respectively. Hence the study recommended the need for increased provision of extension service and training on correct input application and improved farming technologies to increase bean productivity. It also suggested the need for policy to discourage land fragmentation, develop road and market infrastructure in rural areas and encourage further formation of well managed farmer groups to improve production efficiency of bean farms.

Keywords: Common bean, efficiency, stochastic frontier approach, Tobit, Uganda

INTRODUCTION

Poor but developing, Uganda's economy is predominantly agricultural and employs about 70.8% of the population. At the rural household level, the proportion of the population directly involved in agricultural activities is even higher with crop production accounting for more than 70% of the employment within the sector itself. However, about 68.1% depend on agriculture for subsistence, while the rest practice farming for commercial purposes (FAO, 2009). In general, the sector accounts for 25% of the Gross Domestic Product (GDP), (UBOS, 2010) and serves as an important provider of inputs for the other production activities, especially the manufacturing sector. Moreover, 80% of the Ugandan population live in rural areas and depend almost entirely on Agriculture for their livelihoods; hence the sector serves as a basic source and provider of food self-sufficiency and security for majority of the population (UBOS, 2010).

With respect to Common bean (*Phaseolus vulgaris* L.), (Maayo *et al.*, 2007) document that it is the most widely grown pulse, second only to maize as a food crop and a major source of food security in East Africa. It is readily available and a popular food to both the urban and rural populations in Uganda. In addition, according to Kara *et al.* (2009) it is consumed by people from all income levels and serves as a primary

source of dietary protein for people in the lower income bracket. Shelled beans are richer than green beans. The former provide about 25% of the total calories and 45% of the protein intake of the diets of many Ugandans (Gepts, 1998). The crop is also included in the daily diets of more than 300 million people worldwide (Golezani *et al.*, 2012).

In addition, Bean is an important source of income for many Ugandan farmers and traders, due to the increasing demand both in the domestic and export markets such as Kenya. And according FAO statistics (FAO, 2009), bean accounted for 6.1% of the total Uganda's agricultural GDP. The crop also ranked fifth behind banana, cassava, indigenous cattle meat and cattle milk in terms of value of output. Similarly, the estimated economic value of total bean output when valued at 2009 market prices was higher than total earnings from coffee, which is Uganda's chief export commodity (FAO, 2009). This implies that harnessing the bean yield potential through increased investment in bean research could lead to significant improvements in the health and wellbeing of many Ugandans (Potts and Nagujja, 2012).

Uganda's total bean output was increasing rapidly between 1997 and 2002 as indicated by FAO statistics in Table 1 (FAO, 2011). These statistics correspond with the introduction of improved and more disease resistant varieties by NARO (National Agricultural

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Table 1: Common bean production information in Uganda for selected years

Year	Output ('000' Mt ¹)	Harvested area ('000' Ha)	Yield (Mt/ha)
1997	221	630	0.35
1998	387	645	0.60
1999	401	669	0.60
2000	420	699	0.60
2001	511	731	0.70
2002	535	765	0.70
2003	525	780	0.67
2004	455	812	0.56
2005	478	828	0.58
2006	424	849	0.50
2007	435	870	0.50
2008	440	896	0.49
2009	452	925	0.49
2010	948	-	-
2011	973*	-	-

(FAO, 2011) *: denotes estimated figures; -: denotes missing data; ¹: Mt denotes metric tonnes, equivalent to 1000 kgs

Research Organization) during the same period (Kalyebara, 2008). In fact, during this period the productivity per hectare was also increasing every year. However, subsequent years (from 2002 to 2006) saw a series of fluctuations in bean output, resulting in a general decline in domestic food supply per capita during the same period. And even as statistics for 2006 to 2011 reveal an upward trend in bean output; the country's productivity per hectare has been on the decline since 2001.

FAO statistics (FAO, 2011) also indicate that the area under bean cultivation has been increasing, each year since 1997, which could also explain the increase in output. However, Piya *et al.* (2011) document the importance of increasing land productivity especially as cultivable land continues to be scarce over time. Another concern is that the country's forests cover is continuously being reduced as a result of agricultural expansion; and hence improving productivity in agriculture and particularly in bean farming is an inevitable step to salvage the forest resources. Moreover, the potential productivity level of the crop is yet to be achieved; since the average bean yield has been recorded as 0.6-0.8 Mt/Ha, although yields of 1.5-2.0 Mt/Ha can be realized with improved varieties and good crop husbandry (Kalyebara, 2008). In fact, yields as high as 5 Mt/Ha have been achieved in some countries like Mexico under farmer management (Muasya, 2001). Despite the longer and warmer nights, lower radiation in the tropics, as well as several other policy and institutional challenges, it is possible to achieve such high yields in Uganda.

Coincidentally, the current policy thrust with respect to agriculture is aimed at modernization of the sector (MAAIF, 2004). Therefore various stakeholders such as CIAT (International Center for Tropical Agriculture) have come up with programmes to scale up livelihoods of smallholder farmers through a market-

led approach. Specifically, CIAT, NARO and other partners have been promoting productivity enhancing technologies and creating an enabling environment for farmers in Eastern Uganda over the past three years. However, the effectiveness of this intervention in improving sustainable bean productivity has not been evaluated. Past studies on common bean in Uganda have also not focused on production efficiency. Therefore, this study investigated the factors influencing bean productivity and technical efficiency among smallholder farmers in Eastern Uganda. Bearing in mind that technical efficiency is the ability of a common bean farm to produce the maximum possible yield given the available production inputs and technology.

Empirical findings from this study provide government and other stakeholders with the needed evidence towards the achievement of the first and seventh millennium development goals; of eradicating poverty and hunger and ensuring environmental sustainability respectively.

MATERIALS AND METHODS

Study area: This study was conducted in the Eastern region of Uganda which is generally suitable for common bean production; hence it was appropriate for this study. Specifically, the study focused on four representative districts namely: Mbale, Tororo, Busia and Budaka because bean production is high in these areas (over 80%) and also since they were incorporated in the INSPIRE (Integrated Soil Productivity Initiative through Research and Education) project by CIAT and partners, which was the basis of this study.

The study area covered two Agro-Ecological Zones (AEZ). The Montane AEZ, in which Mbale falls, is found at higher elevations between 1500-1700 metres above sea level and receives high and effective rainfall. In addition, the soils in this zone are majorly volcanic with medium to high productivity. On the other hand, the Banana-millet-cotton AEZ covers (but it is not limited to) Tororo, Busia and Budaka districts and it is found at lower elevations with less evenly distributed rainfall, ranging between 1000-1500mm p.a. The soils in this zone are a mixture of volcanic and alluvial with low to medium productivity. The major staple crops grown in the districts include: bananas, sweet potatoes, cassava, Irish potatoes and beans. Other crops grown include coffee, wheat, barley, maize, millet, peas, 'simsim', sunflower, cotton, rice, onions and carrots (Mwebaze *et al.*, 1999).

Uganda's bean production is mainly dominated by small scale farmers, who have limited resources and produce the crop under unfavourable conditions (e.g. low use of inputs, marginal lands and intercropping with competitive crops). The average plot size for these

farmers ranges from 0.1 to 0.5 ha per household (Soniia and Michiel, 1997).

Data: The population of interest constituted smallholder producers of common bean in Eastern Uganda, while the sampling unit was the farm household. For sampling purposes a multistage sampling technique was employed involving purposive sampling of four districts in Eastern Uganda; after which a simple random sampling procedure was used at the sub-county, parish and village levels for each district. Then a sample of 280 households was randomly selected using a list of farmers in the village for purposes of the study.

Primary data was collected for the 2010 season using personally administered structured questionnaires and through observation method. The data included information on common bean farming operations such as: quantities of seeds, planting and top dressing fertilizer, pesticides, herbicides, fungicides, manure, land area and labour man-days. Corresponding information on average input prices was also collected from the respondents. The land area under beans (hectares) was then used to standardize the rest of the inputs, so that each input was considered in terms of the quantities per hectare. Additional data focused on household socio-economic and institutional characteristics such as the farmer's age, gender, years of schooling, farming experience, main occupation, household size, the income and asset profiles, distance to the market, extension contacts, group membership and credit.

ANALYTICAL FRAMEWORK: STOCHASTIC FRONTIER MODEL

The history of stochastic models began with Aigner and Chu (1968) who suggested a composite error term and since their study much effort has been exerted to finding an appropriate model to measure technical efficiency. There are two approaches to estimating technical efficiency: the parametric and non-parametric approaches (Sephehdoust, 2011). The stochastic production frontier developed by Meeusen and Van Den Broeck (1977) follows the parametric approach; while the Data Envelopment Analysis (DEA) developed by Charnes *et al.* (1978) follows the non-parametric approach. In this study we adopt the stochastic frontier approach due to its simplicity.

The stochastic frontier model is an improvement to the deterministic model since it introduces 'v' into the deterministic model to form a composite error term model (stochastic frontier). The error term in the stochastic model is assumed to have two additive components namely: a symmetric component which represents the effect of statistical noise (such as

weather, topography, measurement error and so on). The other error component captures systematic influences that are unexplained by the production function and are attributed to the effect of technical inefficiency (Binuomote *et al.*, 2008). The model is as specified below:

$$Y = f(x, \beta)e^{v-\mu} \quad (1)$$

where,

$f(x, \beta)$ = The production function

$v-\mu$ = The error term. Empirically

Y_i = The bean output (90 kg bags)

X_1 = The plot size (ha)

X_2 = Labour (man-days)

X_3 = Fertilizer (Kgs)

X_4 = Chemical inputs (pesticides, fungicides, herbicides)

X_5 = Seeds (Kgs)

X_6 = Manure (Kgs)

It is expected that the more inputs used by the farmer, the higher the bean yields. Although for chemical inputs and labour, increased usage may produce negative effects on outputs if the farm has reached diminishing returns with respect to that input. The U_i in Eq. (1) captures the level of farm-specific technical inefficiency and V_i is the statistical disturbance term. The V_i 's are random variables which are assumed to be iid (Independent and Identically distributed) $N(0, \delta V^2)$ and independent of the U_i 's which are non-negative random variables assumed to account for technical inefficiency in production and are often assumed to be iid $N(0, \delta u^2)$. The estimated value of technical efficiency for each observation is then calculated as follows:

$$TE_i = \exp(-U_i) \quad (2)$$

While the unobservable value of V_{it} is obtained from its conditional expectation given the observable value of (V_i-U_i) in equation 1 as suggested by Yao and Liu (1998). It is thus clear that if U_i does not exist in Eq. (1) or $U_i = \delta_0^2 = 0$, the stochastic frontier production function reduces to a traditional production function. In that case, the observed units are equally efficient and residual output is solely explained by unsystematic influences. The distributional parameters U_i and δu^2 are hence inefficiency indicators, the former indicating the average level of technical inefficiency and the latter representing the dispersion of the inefficiency level across observational bean farms (Tijani, 2006).

Thus given functional and distributional assumptions, the values of unknown coefficients in Eq. (1) (i.e., β_s , δu^2 and δv^2) are obtained using the maximum Likelihood Method (ML). It is further assumed that the average level of technical efficiency,

predicted as TE_i in Eq. (2) is a function of socio-economic and institutional factors. However, in this study, the factors influencing efficiency were determined using a two-limit Tobit model since the technical efficiency scores range between 0 and 1 depicting the upper and lower limits. The approach has been applied by other authors such as Nyagaka *et al.* (2009).

TOBIT MODEL

The structural equation of the Tobit model is given as:

$$y_i^* = Z_i\beta + \varepsilon_i \quad (3)$$

where, y_i^* is a latent variable for the i^{th} bean farm that is observed for values greater than τ and censored for value less than or equal to τ . The Tobit model can be generalized to take account of censoring both from below and from above. Z is a vector of independent variables postulated to influence efficiency. The β 's are parameters associated with the independent variables to be estimated. The ε is the independently distributed error term assumed to be normally distributed with a mean of zero and a constant variance. The observed y is defined by the following generic measurement equation:

$$\begin{aligned} y_i &= y_i^* \text{ if } y_i^* > \tau \\ y_i &= \tau_y \text{ if } y_i^* \leq \tau \end{aligned} \quad (4)$$

Typically, the Tobit model assumes that $\tau = 0$ which means that the data is censored at zero. However, as mentioned earlier farm-specific technical efficiency scores range between 0-1. Thus we substitute τ in Eq. (4) as follows:

$$\begin{aligned} y_i &= y_i^* \text{ if } 0 < y_i^* < 1 \\ y_i &= 0 \text{ if } y_i^* \leq 0 \\ y_i &= 1 \text{ if } y_i^* \geq 1 \end{aligned} \quad (5)$$

Therefore the model assumes that there is an underlying stochastic index equal to $(Z_i\beta + \varepsilon_i)$ which is observed only when it is some number between 0 and 1; otherwise y_i^* qualifies as an unobserved latent (hidden) variable. The dependent variable is not normally distributed since its values range between 0 and 1. The empirical Tobit model for this study therefore takes the following form:

$$y_i^* = \beta_0 + \sum_{n=1}^{11} \beta_n Z_i + \varepsilon_i \quad (6)$$

where,

Z_1 = Age of the farmer (years) is expected to have a negative effect on technical efficiency because

older farmers are risk averse making them late adopters of better agricultural technologies.

Z_2 = Farming experience (years) is expected to positively influence technical efficiency because experienced farmers are better producers, who have learned from their past mistakes; hence they make rational decisions compared to less experienced farmers.

Z_3 = Education (years of schooling) is expected to have mixed results; since on the one hand, educated farmers committed in farming may be able to take up improved technologies faster because they understand the benefits associated with the technology, hence increasing their efficiency. On the other hand, educated farmers may be more engaged in other income generating activities and avail less attention to their farms, hence lowering their efficiency.

Z_4 = Gender of household head (1 = if female and 0 = otherwise) is also supposed to have a negative relationship with technical efficiency because female farmers are faced with more challenges compared to the male farmers in terms of access to information and resources and also due to their responsibilities in the home.

Z_5 = Off-farm income (Ush) is hypothesised to have a positive effect on technical efficiency; since farmers with such incomes have a regular source of income that they can use to acquire farm inputs.

Z_6 = Market Access (km) is expected to have a negative influence on technical efficiency, since nearness to markets increases access to inputs and credit hence improving farm technical efficiency.

Z_7 = Credit access (Ush) is hypothesised to have a positive effect on technical efficiency, because such funds help farmers to overcome liquidity problems that normally hinder them from purchasing inputs when they are available cheaply. As such credit assists farmers to be ready with necessary inputs in time for planting immediately the rains come.

Z_8 = Group membership (1 = if yes and 0 = if no) is expected to have a positive influence on technical efficiency. This is because it helps farmers to mitigate problems associated with market imperfections and reduce transaction costs, hence increasing technical efficiency.

Z_9 = Assets owned (Ush) is expected to have a positive effect on farm technical efficiency. Specifically, bicycles and motor vehicles help farmers to move easily to the market, radios and televisions help farmers to access information through the media, while mobile phones assist the farmers to communicate and exchange information quickly. As such, the assets combine to make the farm more efficient.

Z₁₀ = Main occupation of the farmer (1 = if farming and 0 = otherwise) is hypothesised to show negative influence on technical efficiency. In other words, farmers whose main occupation is farming are expected to have lower efficiency than those engaging in employment or businesses as well. This is because the latter are more able to finance their farming activities. Lastly,

Z₁₁ = Farm size (hectares) is hypothesised to have a positive influence on technical efficiency, given that larger farmers are expected to portray economies of scale in their farming operations compared to smaller farms.

It is important to mention that estimating the model using OLS would produce both inconsistent and biased estimates. This is because OLS underestimates the true effect of the parameters by reducing the slope (Gujarati, 2003). Therefore, the maximum likelihood estimation is recommended for Tobit analysis.

RESULTS AND DISCUSSION

Bean production characteristics: The bean productivity results are as presented in Table 2. Bean

production levels in Eastern Uganda are very low given that the average yield per hectare among all the farmers was 0.47 mt/ha. This productivity level is low compared to the country's average productivity ranging between 0.6-0.8 mt/ha, but is much lower than the potential productivity level in Uganda which is 1.5-1.8 mt/ha. In terms of districts, Mbale had the highest mean productivity of 0.53 mt/ ha, followed by Busia with a mean of 0.45 mt/ha, Tororo with a mean of 0.44 mt/ha while Budaka had the least average productivity (0.37 mt/ha). This is supported by the fact that Mbale district is located within a more productive agro-ecological zone unlike the other three districts.

Moreover, participants in the INSPIRE intervention showed higher levels of bean productivity with a mean of 0.51 mt/ha, compared to non-participant farmers who showed a mean productivity of 0.36 mt/ha. In addition, the t-test to compare the means for the two farmer categories was significant at 1% level, an indication that participant farmers were significantly better bean producers than non-participants.

In terms of the total farm size the findings (Table 3) indicate that participant farmers had a mean of 1.88

Table 2: Bean productivity information

Variables		Overall	Participants	Non-participants	t	Sig.
Total sample	Mean	0.47	0.52	0.40	3.434	0.001***
	Standard deviation	0.32	0.35	0.27		
Busia district	Mean	0.45	0.51	0.36	3.349	0.001***
	Standard deviation	0.31	0.34	0.24		
Mbale district	Mean	0.53	0.54	0.52	0.197	0.844
	Standard deviation	0.39	0.45	0.34		
Budaka district	Mean	0.37	0.41	0.31	0.596	0.559
	Standard deviation	0.35	0.39	0.30		
Tororo district	Mean	0.44	0.55	0.33	2.541	0.015**
	Standard deviation	0.30	0.29	0.26		

** , *** is significant at 5% and 1% level respectively

Table 3: Summary of continuous production characteristics

Variables		Overall	Participants	Non-part'	t	Sig.
Farm size (Hectares)	Mean	1.69	1.88	1.45	2.281	0.023**
	Standard deviation	1.63	1.80	1.34		
Area planted (Hectares)	Mean	0.36	0.37	0.36	0.173	0.863
	Standard deviation	0.28	0.29	0.26		
Seeds used (kg/ha)	Mean	34.08	34.82	33.13	0.640	0.523
	Standard deviation	21.91	22.55	21.10		
Plant' fertilizer (kg/ha)	Mean	89.10	90.50	87.28	1.142	0.254
	Standard deviation	23.70	24.93	21.99		
Topdressing (kg/ha)	Mean	91.84	88.82	95.76	-3.885	0.000***
	Standard deviation	15.31	15.51	14.18		
Herbicides (kg/ha)	Mean	27.91	4.80	57.88	-42.249	0.000***
	Standard deviation	27.91	2.18	13.69		
Fungicides (kg/ha)	Mean	14.28	22.84	3.18	24.770	0.000***
	Standard deviation	12.28	9.91	0.71		
Pesticides (Litres/ha)	Mean	5.89	7.40	3.92	9.484	0.000***
	Standard deviation	3.78	4.29	1.47		
Manure (kg/ha)	Mean	295.22	356.62	215.54	7.005	0.000***
	Standard deviation	194.78	226.50	97.70		
Certified seed (kg/ha)	Mean	31.39	27.24	36.77	-5.367	0.000***
	Standard deviation	14.91	12.27	16.29		

** , *** is significant at 5% and 1% level respectively

ha, while non-participant farmers had a mean of 1.45 ha. This implies that participant farmers had significantly larger farm sizes at 5% level than non-participant farmers. Moreover, the findings also showed that on average participant farmers had a mean area under bean production of 0.37 ha, while non-participant farmers had a mean of 0.36 ha.

The mean quantity of seeds used by participant farmers was 34.82 kg/ha compared to non-participant farmers who used an average of 33.13 kg/ha; thus participant farmers used slightly more seeds than the non-participant farmers. Similarly, participant farmers were better in the use of planting fertilizer, with the mean application of 90.50 kg/ha; while non-participant farmers had a mean of 87.28 kg/ha, however both these were not significantly different statistically.

On the other hand, non-participant farmers applied an average of 95.76 kg/ha for topdressing fertilizer compared to participant farmers who applied 88.82 kg/ha. Hence, non-participant farmers applied significantly more topdressing fertilizer than their participant counterparts. The findings also indicate that participant farmers used an average of 4.80 kg of herbicides per ha, whereas non-participant farmers used 57.88 kg/ha on average. The t-test results also show that participant farmers applied significantly less herbicides than their non-participant counterparts. This could be attributed to the fact that there was higher adoption of safe agricultural technologies among participants in the INSPIRE intervention, through which they were able to control weeds without using chemicals.

The findings further reveal that participant farmers applied significantly more fungicides with a mean quantity of 22.84 kg/ha, while non-participant farmers had a mean of 3.18 kg/ha. Similarly, the mean quantity of pesticides used by the participant farmers was 7.40 L/ha, compared to non-participant farmers with a mean of 3.92 L/ha. And lack of adequate knowledge on fungicides and pesticides especially among non-participant farmers may have been responsible for the difference, given the fact that very few of them accessed extension service.

The use of animal manure in crop farming has been highly advocated by environmental activists as a way to improve soil fertility without producing negative externalities to the environment. The results in Table 3 thus show that participant farmers used significantly more quantities of animal manure, with a mean of 356.62 kg/ha compared to non-participant farmers who applied on average 215.54 kg/ha. On the contrary, non-participant farmers applied more certified seeds with a mean of 36.77 kg/ha compared to 27.24 kg/ha reported for the participant farmers. This may be because non-participant farmers had better access to the input

Table 4: Stochastic frontier production function results

Yield/Ha	Coefficient	Z	P> z
Seeds (kg)/Ha	0.385	4.88	0.000***
Plot size (Ha)	0.353	3.68	0.000***
Herbicides (kg)/Ha	0.122	0.91	0.365
Certified seeds (kg)/Ha	0.116	1.95	0.051*
Planting Fertilizer (kg)/Ha	0.110	1.87	0.062*
Labour (man-days)/Ha	0.091	1.12	0.264
Manure (kg)/Ha	0.034	1.03	0.304
Pesticides (Litres)/Ha	-0.004	-0.08	0.938
Topdressing (kg)/Ha	-0.024	-0.35	0.723
Fungicides (kg)/Ha	-0.082	-0.96	0.339
Constant	4.395	12.18	0.000***
(σ_v) ¹	0.706		
(σ_u)	1.123		
(σ^2)	1.760		
(γ)	0.638		

*, **, *** is significant at 10, 5 and 1% level, respectively; ¹(σ_v) is statistical disturbance term; (σ_u) is technical inefficiency term; (σ^2) is variance in bean productivity across farms; and gamma (γ) is the proportion of the variance caused by technical inefficiency

market, but they failed to accompany the certified seeds with enough fertilizer and correct crop husbandry, to warrant better productivity.

Determinants of common bean productivity: To identify the factors affecting bean productivity, a stochastic frontier production function was estimated. Four variables (plot size, seeds, planting fertilizer and certified seed) were found to significantly affect bean productivity. The log likelihood for the fitted model was -448.17 and the chi-square was 95.96 and strongly significant at 1% level. Thus the overall model was significant and the explanatory variables used in the model were collectively able to explain the variations in bean productivity. The model results further show that the variance of the technical inefficiency parameter γ is $0.638 [\gamma = \sigma_u^2/\sigma^2, (Greene, 2011)]$ and is significantly different from zero. This implies that 63.8% of the variations in bean output were due to technical inefficiency. The stochastic frontier production function results are presented in Table 4.

The following elasticities were generated from the stochastic production frontier estimation (Table 3): seeds (0.385), plot size (0.353), herbicides (0.122), certified seeds (0.116), planting fertilizer (0.110), labour (0.091), manure (0.034), pesticides (-0.004), topdressing fertilizer (-0.024) and fungicides (-0.082). Hence, the resulting returns to scale parameter obtained by summing these input elasticities is 1.101. This indicates that bean production in Eastern Uganda exhibits constant returns to scale, implying that farmers in the study area use traditional bean production techniques which have become redundant over time; although if they embraced the technological changes they can improve their productivity. Seed had the largest elasticity, followed closely by plot size. This

suggests that any interventions to increase productivity of seed and plot size would create significant achievements in bean productivity in Eastern Uganda. Similar to findings by Ajani and Ugwu (2008), the elasticities for pesticides, top-dressing fertilizer and fungicides were negative. Hence increased quantities of these inputs will reduce the bean productivity in the area.

The results showed a positive coefficient for seeds as was hypothesised. Seeds had a strongly significant effect on bean productivity at 1% level. The results showed that a 1% increase in the quantity of seeds used significantly increased bean yields by 38.5%. These findings coincide with those by Nya *et al.* (2010) who found that improved planting materials like cuttings or seeds significantly influenced yields and profitability among vegetable farmers in Southern Nigeria. The results suggest that planting more seeds improved bean productivity significantly, which is attributed to the fact that the increased number of seeds per hole helped reduce the risk of plants failing to sprout and translated into higher production from a unit piece of land. Given that seed had the largest elasticity; it might also imply that seed was the major limiting factor of production that constrained bean farmers from maximizing their output. The importance of seeds in determining productivity has also been emphasised by Reardon (1996), although it is important to note that for seed to make its full contribution to bean productivity in Sub-Saharan Africa, the farmers need to use certified seeds which have an assurance of quality. However, the seed variety used is also important in determining the contribution of seeds to bean productivity. Better and improved seed varieties may be able to produce high yields even without planting many seeds per hole.

The findings also showed a positive coefficient for plot size as was postulated. Plot size has a strongly significant influence on common bean productivity at 1% level. According to the results, an increase in the plot size by 1% significantly increased the farmer's bean productivity by 35.3%. This suggests that the more farm land a farmer allocated to bean farming, the higher the yields obtained, which presents similar findings as those reported by Koc *et al.* (2011). The authors argued that most smallholder farmers usually fail to maximize bean yields due to underutilization of farm land. This might be due to limited availability of other production factors or due to farmers' risk averseness coupled with rainfall fluctuations brought about by climate change. However, Ugwumba (2010) in Nigeria observed that land was underutilized mainly due to land tenure problems associated with land fragmentation. Therefore based on the results it is implied that as the sizes of land holding continue to

decline, it is increasingly going to become difficult to increase productivity through expansion in plot sizes.

Certified seed also showed a positive effect on bean productivity according to the findings. It was established that certified seed had a significant influence on bean yields at 10% level, since a 1% increase in the quantity of certified seed used increased bean productivity by 11.6%. This suggests that the more certified seeds a farmer was able to apply on the farm, the higher were the bean outputs. Despite this finding, it was observed that most farmers use recycled seed varieties for their home consumption and certified seed only for commercial bean production. This is mainly because improved seed varieties are quite costly, compared to recycled seeds. The behaviour may also be attributed to ineffectiveness in the seed distribution systems and lack of timely availability of the seeds during the planting season (Reardon, 1996).

It was further found that planting fertilizer showed a positive coefficient as hypothesised, with a significant relationship with bean yields at 10% level. The results revealed that a 1% increase in the quantity of planting fertilizer applied, significantly improved bean productivity by 11%. This suggests that increasing the amount of planting fertilizer used would contribute to higher bean yields in the area by a factor of 10. The results are consistent as hypothesised and they reflect the findings presented by Tchale (2009) in Malawi where fertilizer was a key factor in production of major crops grown by smallholder farmers. Reardon (1996) also found a positive effect of fertilizer on productivity in case studies from Burkina Faso, Senegal, Rwanda and Zimbabwe. However, the findings contradict (Kijima *et al.*, 2011) who observed that soils in Uganda were fertile enough and could produce relatively high yields even without adequate fertilizer use. As such, from the results it is evident that to achieve higher bean productivity, farmers in Eastern Uganda need to increase their usage of planting fertilizer.

The other variables were found to have an insignificant influence on bean yields. For instance, herbicides, manure and labour had a positive influence on bean yields as hypothesised; while topdressing fertilizer, fungicides and pesticides had a negative influence according to the findings. The negative sign for topdressing fertilizer, fungicides and pesticides may be attributed to the fact that there was limited knowledge among farmers about the right proportions of these inputs to apply; hence they may have over-applied it leading to negative effects on yields.

Farm-specific technical efficiency scores: Predicted farm-specific technical efficiency scores for sampled bean farms in Eastern Uganda were predicted after

Table 5: Predicted technical efficiency scores across intervention participants and non-participant farmers

TE	Participants		Non-participants	
	Frequency	%	Frequency	%
Class				
0-24	25	15.92	18	14.88
25-49	45	28.66	38	31.40
50-74	78	49.68	58	47.93
75-100	9	5.73	7	5.79
Total	157	100	121	100
Mean		48.71		47.54
Standard deviation		21.48		20.44
Maximum		83.67		85.32
Minimum		0.51		0.91
t-ratio				0.463
Sig.				0.643
Overall mean				48.20

Table 6: Farm-specific efficiency scores across districts

District	TE		ANOVA	
	Mean (%)	S.D	F-ratio	Sig.
Mbale	51.84	19.44	1.595	0.191
Busia	48.48	21.60		
Tororo	45.39	21.79		
Budaka	41.44	17.02		

t- test for Mbale and Budaka: t-ratio = 2.208; Sig = 0.035**

** : Is significant at 5% level

Table 7: To bit regression estimates of factors influencing technical efficiency

TE	Coefficient	t	P> t
Sex (1 = female)	0.020	0.720	0.472
Age (years)	-0.002	-1.720	0.086*
Schooling (years)	0.002	0.510	0.609
Occupation (1 = farming)	0.000	-0.070	0.947
Farming (years)	0.000	0.440	0.659
Farm size (ha)	0.015	1.810	0.071*
Off-farm Income (Ush)	0.017	1.640	0.103
Asset value (Ush)	0.024	2.910	0.004***
Distance to market (km)	-0.008	-2.360	0.019**
Extension service	0.064	2.550	0.011**
Group membership	0.144	2.030	0.044**
Credit (Ush)	-0.001	-0.680	0.498
Constant	0.060	0.430	0.669
Log likelihood =	58.019	41.460	
Pseudo R ² =	-0.556	0.000	

*, **, *** Is significant at 10, 5 and 1%, respectively

estimating the stochastic frontier production function. The mean technical efficiency score for all the sampled farms was 48.20%, with participant farms showing a higher mean (48.71) than the overall; while the mean for non-participant farmers was lower than the overall at 47.54%. However, subsequent t-test results revealed that the mean difference in technical efficiency between participants and non-participant farmers was statistically insignificant. The technical efficiency scores for sampled bean farms in Eastern Uganda are summarized in Table 5.

The most technically efficient farm among participant farms had a score of 83.67% compared to

the most efficient for non-participant farms with a score of 85.32%. The least technically efficient participant farm recorded a score of 0.51% while the least score for non-participant farms was 0.91%. These scores give evidence that there is a very huge gap between the two extreme farms in terms of technical efficiency among both categories of farmers. However, if an average bean farm were to achieve the level of technical efficiency shown by the most efficient farm, then they could realize a saving of 43.51% in terms of reduced yield loss $[(1-(48.20/85.32)) \times 100]$.

It is also evident (Table 5) that 15.92% of the participant farms had TE levels less than 25%; which is a larger proportion than 14.88% among non-participant farms. The proportion of farmers in the highest class was 5.73% for participants and 5.79% for non-participants. In addition, about 55.41% of the participants and 53.72% of the non-participants had TE levels above the 50% limit. It is therefore implied that about half of the farms are in the upper two classes and can easily improve their technical efficiency level to that showed by the most efficient farm.

Across the districts focused in the study, the ANOVA results (Table 6) revealed that technical efficiency levels did not vary significantly across districts. However, mean results indicate that Mbale had the highest average technical efficiency levels (51.84%) among bean farms, while Budaka had the least efficient bean farms with a mean of 41.44%. A subsequent t-test also indicated that the difference in average technical efficiency levels between Mbale and Budaka was significant at 5% level. This is attributed to the fact that Mbale showed the highest bean productivity per hectare, while Budaka was the least productive (Table 2).

Determinants of technical efficiency: The results in Table 7 show the estimates from the two-limit Tobit regression of selected socio-economic and institutional-support factors against predicted technical efficiency scores. The model was correctly estimated since the model chi-square was 41.46 and it was strongly significant at 1% level. In addition, the pseudo R² was 55.6%, against the recommended level of 20%. Thus it is evident that the explanatory variables chosen for the model were able to explain 55.6% of the variations in technical efficiency levels. Among the selected variables, six were found to have a significant contribution on technical efficiency namely: age, farm size, asset value and distance to the input market, extension services and group membership.

Age of the household head showed a negative effect on technical efficiency of the bean farms as was hypothesised and it was significant at 10% level. The

results revealed that an increase in the farmer's age by one year reduced the level of technical efficiency by 0.2%. This means that older farmers were less technically efficient in bean production than their younger counterparts consistent with findings by Kibaara (2005) in Kenya. The finding is attributed to the fact that older bean farmers in the study area are relatively more reluctant to take up better technologies, instead they prefer to hold to the traditional farming methods thus become more technically inefficient compared to their younger counterparts. This reluctance to embrace innovative farming methods is also responsible for the constant returns to scale realized earlier. However Illukpitiya (2005) and Piya *et al.* (2012) found contradicting results in Sri-lanka and Nepal respectively, where it was observed that elderly farmers had a wealth of experience and therefore were technically more efficient in production than their younger counterparts. The inconsistency may be due to differences in socio-economic characteristics of the sampled farmers, however, it is important to emphasize that being older may not always mean being more experienced.

Farm size was found to have a positive effect on technical efficiency as hypothesised and it was significant at 10% level. According to the results, an increase in the size of the farm by a hectare increased farm technical efficiency by 1.5%. It may be argued that farmers with larger farms are more able to use the land sparingly, which reduces the loss in soil fertility level on their farm land, hence making them more productive. The opposite is true for farmers with small units of land, since the land is cultivated every year reducing its productivity and hence increasing technical inefficiency. The results also concur with those by Ghorbani *et al.* (2009) in Malaysia; and Alemdar and Oren (2006) in Turkey. However, they are contrary to a number of studies that have been done in other countries or in different crops. For instance Edeh and Awoke (2009) among cassava farmers in Nigeria; (Tchale, 2009) among smallholder crop farmers on Malawi; and Aggrey *et al.* (2010) among East African manufacturing firms. Despite this inconsistency, the findings obtained in this study make sense since they re-emphasizes that land fragmentation commonly practiced in many rural areas has a negative effect on agricultural productivity.

The value of assets owned also showed a positive effect on technical efficiency as hypothesised and was significant at 1% level. The results indicated that a unit increase in the value of assets owned by a household increased technical efficiency by 2.4%. The positive contribution of these assets can be considered with respect to their respective functions. For instance, assets

like motor vehicles, motor cycles, bicycles and animal carts provide a means for farmers to move easily or ferry their produce to the market. They can also help in provision of income that enhances the available capital and improves farming investments. Furthermore, communication devices like mobile phones help farmers to easily exchange valuable information on farming. Radios and televisions also provide useful information through the media, which farmers incorporate in their farming activities, hence improving their technical efficiency. Tchale (2009) also found similar findings among smallholder crop farmers in Malawi, where he observed that assets owned by the farm household normally serve as security to guarantee access to loans by farmers, which ensures availability of funds to acquire farm inputs, hence increasing the farm's technical efficiency.

Further findings indicate that distance to the input market showed a negative effect on technical efficiency as earlier expected and it was significant at 5% level. It was found that an increase in the distance to the market by one kilometre; lead to a decrease in the farm's technical efficiency by 0.8%. The result is attributed to the fact that a farm located far from the market incurs more costs to transport farm inputs from the market, compared to the one closer to the market. This in turn hinders the optimal application of farm inputs and leads to technical inefficiency.

The findings are consistent with results found by Bagamba *et al.* (2007) among smallholder banana producers in Uganda. They observed that households located nearer to the factor markets showed higher technical efficiency than those located in remote areas. According to the authors, proximity (nearness) to the factor market increased farmers' ease of accessing farm inputs and extension trainings from which they could attain information and skills for better crop management hence increasing their productivity.

Extension services also showed a positive and significant influence on technical efficiency at 5% level. According to the findings, bean farmers who accessed extension services showed a higher level of technical efficiency by 6.4%, than those who failed to access the services. This suggests that access to extension services enabled bean producers to obtain information on crop diseases or pests and their control methods; as well as insights on innovative farming techniques that guarantee higher productivity. Similar findings were reported by Illukpitiya (2005) among rural households in Sri-lanka. Illukpitiya argued that farmers who received extension service were more knowledgeable on new and improved farming practices hence they showed higher technical efficiency levels. In addition, Al-Hassan (2008) observed that farmers who

get adequate extension contacts are able to access modern agricultural technology for input mobilization, input use and disease control, which enable them to reduce technical inefficiency.

Technical efficiency was further influenced by whether a bean farmer participated in producer groups or not. According to the findings, group membership showed a positive and significant relationship at 5% level; such that farmers who were members in a producer group improved their technical efficiency levels by 14.4% compared to those who failed to join farmer groups. The importance of membership in farmer organizations was also reported by Idiong (2007) among smallholder swamp rice producers in Nigeria; and Tchale (2009) among smallholder crop producers in Malawi. Collectively they observed that farmers who are members in producer organizations are able to benefit not only from the shared knowledge among themselves with respect to modern farming methods, but also from economies of scale in accessing input markets as a group. Hence, such farmers become more technically efficient in production.

CONCLUSION AND RECOMMENDATIONS

Conclusion: The main objective dealt with in this study was to determine the factors influencing common bean productivity and technical efficiency among smallholder farmers in Eastern Uganda. It was established that bean productivity was significantly influenced by plot size, ordinary seeds, certified seeds and planting fertilizer; all of which had a positive effect as hypothesised. Further results revealed that the mean technical efficiency among bean farms was 48.2%. However, there were large discrepancies between the most technically efficient and the least technically efficient farms. It was also encouraging that at least half of the farms had technical efficiency scores exceeding the 50% limit and could easily improve to the level of the most efficient farm. Finally, the Tobit regression model estimation revealed that technical efficiency was positively influenced by value of assets (at 1% level), extension service and group membership (at 5% level); and negatively influenced by age and distance to the factor market at 10 and 5% levels respectively.

Recommendations: In the context of bean production, the maximum possible yield per ha is yet to be achieved. Therefore, there is need for the Ministry of Agriculture Animal Industry and Fisheries (MAAIF) to sensitize farmers on the importance of adopting soil enhancing technologies to enhance retention of soil fertility. MAAIF is also obliged to provide more extension service and training to farmers about correct

input application and also concerning improved seed varieties that have disease resistant and high productivity traits. On the other hand, the National Beans Programme concerned with carrying out research in the country needs to have proper mechanisms of disseminating new seed varieties to farmers all over the country. It is further necessary for farmers to allocate more of the available farm land to bean production or apply relay cropping and increase application of fertilizers so as to increase bean productivity to the potential level.

With respect to technical efficiency, the government of Uganda needs to introduce policies and sensitize farmers against land fragmentation since this would help reduce technical inefficiency. There is also need for stakeholders in the Agricultural sector to organize seminars for farmers to be trained on entrepreneurship so that they can invest their farm profits into more farming equipment and income generating assets so as to improve their productivity and harness more farming capital respectively. The Ugandan Ministry of Transport and Works should also develop better roads and market infrastructure in the rural areas to attract private investors, as a way to reduce the distance farmers have to cover to the market. In addition, there is need for MAAIF and other stakeholders to come up with strategies aimed at encouraging farmers to form more well managed producer groups and networks as avenues for accessing inputs, output markets as well as credit facilities to invest in farming. In so doing, bean farmers in Eastern Uganda will become more technically efficient in production.

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REFERENCES

- Aggrey, N., L. Eliab and S. Joseph, 2010. Firm size and technical efficiency in East African manufacturing firms. *Curr. Res. J. Econ. Theory*, 2: 69-75.
- Aigner, D.J. and S.F. Chu, 1968. On estimating the industry production function. *Am. Econ. Rev.*, 58: 826-839.
- Ajani, O.I.Y. and P.C. Ugwu, 2008. Impact of adverse health on agricultural productivity of farmers in Kainji basin North-Central Nigeria using a stochastic production frontier approach. *Trends Agric. Econ.*, 1: 1-7.

- Alemdar, T. and M.N. Oren, 2006. Determinants of technical efficiency of wheat farming in Southeastern Anatolia, Turkey: A nonparametric technical efficiency analysis. *J. Appl. Sci.*, 6: 827-830.
- Al-Hassan, S., 2008. Technical Efficiency of Rice Farmers in Northern Ghana. AERC Research Paper Tamale, Ghana.
- Bagamba, F., R. Rued and R. Mariana, 2007. Determinants of Banana Productivity and Technical Efficiency in Uganda. In: Smale, M. and W.K. Tshemereirwe (Eds.), *An Economic Assessment of Banana Genetic Improvement and Innovation in the Lake Victoria Region of Uganda and Tanzania*. SAGE Publications, Thousand Oaks, California, pp: 109-128.
- Binuomote, S.O., J.O. Ajetomobi and A.O. Ajao, 2008. Technical efficiency of poultry egg producers in Oyo state of Nigeria. *Int. J. Poultry Sci.*, 7(12): 1227-1231.
- Charnes, A., W.W. Cooper and E. Rhodes, 1978. Measuring the efficiency of decision making units. *Europ. J. Oper. Res.*, 2: 429-444.
- Edeh, H.O. and M.U. Awoke, 2009. Technical efficiency analysis of improved cassava farmers in Abakaliki local government area of Ebonyi State: A stochastic frontier approach. *Agric. J.*, 4: 171-174.
- FAO, 2009. Uganda's Country Profile. Food and Agricultural Organization. Retrieved from: <http://www.fao.org/es/ess/top/country.html>.
- FAO, 2011. Uganda's Country Profile. Food and Agricultural Organization. Retrieved from: <http://www.fao.org/es/ess/top/country.html>.
- Gepts, P., 1998. Origin and evolution of common Bean: Past events and recent trends. *Hort. Sci.*, 33: 1124-1130.
- Ghorbani, A., S.A. Mirmahdavi and E. Rahimabadi, 2009. Economic efficiency of Caspian cattle feedlot farms. *Asian J. Anim. Sci.*, 3: 25-32.
- Golezani, K.G., N.N. Rashidabad and S.Z. Salmasi, 2012. Effects of salinity on yield and yield components of pinto bean cultivars. *Int. J. Plant Anim. Environ. Sci.*, 2: 2231-4490.
- Greene, W., 2011. Limited Dependent Models: Censoring, Truncation and Sample Selection. In: Liu, C., J. Chang and A. Yang (Eds.), *Econometric Analysis*. Prentice Hall, USA.
- Gujarati, D., 2003. *Basic Econometrics*. 4th Edn., McGraw-Hill, New York, USA., pp: 192, ISBN-10: 0072427922.
- Idiong, I.C., 2007. Estimation of farm level technical efficiency in small-scale swamp rice production in cross river state of Nigeria: A stochastic frontier approach. *World J. Agric. Sci.*, 3: 653-658.
- Illukpitiya, P., 2005. Technical efficiency in agriculture and dependency on forest resources: An economic analysis of rural households and the conservation of natural forests in Sri Lanka. Economy and Environment Program for Southeast Asia, EEPSEA, Technical Report. Retrieved from: www.idrc.ca/en/ev-99958-201-1-Do-TOPIC.html.
- Kalyebara, M.R., 2008. The Impact of Improved Bush Bean Varieties in Uganda. Network on Bean Research in Africa, CIAT, Kampala, Uganda. Retrieved from: <http://www.ciat.cgiar.org/work/Africa/Documents/highlight43.pdf>.
- Kara, R., T.J. Dalton and A.M. Featherstone, 2009. A nonparametric efficiency analysis of bean producers from North and South Kivu. Proceeding of the Southern Agricultural Economics Association Annual Meeting. Atlanta, Georgia, July 26-28.
- Kibaara, B., 2005. Technical Efficiency in Kenyans' Maize Production: An Application of the Stochastic Frontier Approach. Tegemeo Institute of Agriculture Policy and Development, Colorado State University. Retrieved from: <http://www.tegemeo.org/viewdocument.asp?ID=116>.
- Kijima, Y., K. Otsuka and D. Sserunkuuma, 2011. An inquiry into Constraints on a green revolution in Sub-Saharan Africa: The case of NERICA rice in Uganda. *World Dev.*, 39: 77-86.
- Koc, B., M. Gul and O. Parlakay, 2011. Determination of technical efficiency in second crop maize growing farms in Turkey: A case study for the East Mediterranean in Turkey. *Asian J. Anim. Vet. Adv.*, 6: 488-498.
- MAAIF, 2004. *Agricultural Production Series*. Ministry of Agriculture, Animal Industry and Fishery.
- Mauyo, L.W., J.R. Okalebo, R.A. Kirkby, R. Buruchara, M. Ugen *et al.*, 2007. Technical efficiency and regional market integration of cross-border bean marketing in western Kenya and eastern Uganda. *Afr. J. Bus. Manag.*, 1(4): 77-84.
- Meeusen, W. and J. Van Den Broeck, 1977. Efficiency estimation from a Cobb-Douglas production function with composed error. *Int. Econ. Rev.*, 18: 435-444.
- Muasya, R.M., 2001. Crop physiological analysis of seed quality variation in 'common' beans (*Phaseolus vulgaris* L.). Ph.D. Thesis, Wageningen University, Netherlands.
- Mwebaze, M.N.S., J.M. Suttie and S.G. Reynolds, 1999. *Country Pasture/ Forage Resource Profiles for Uganda*. Department of Animal Production and Marketing, MAAIF, Entebbe, Uganda.
- Nya, E.J., N.U. Okorie and M.J. Eka, 2010. An economic analysis of *Talinum triangulare* (Jacq.) production /farming in southern Nigeria. *Trends Agric. Econ.*, 3: 79-93.

- Nyagaka, D.O., G.A. Obare and W. Nguyo, 2009. Economic efficiency of smallholder Irish potato producers in Kenya: A case of Nyandarua north district. Proceedings of the International Conference Association of Agricultural Economists., Beijing, China, August 16-22.
- Piya, S., A. Kiminami and H. Yagi, 2011. Sources of agricultural productivity growth in south and Southeast Asia. *Trends Agric. Econ.*, 4: 18-29.
- Piya, S., A. Kiminami and H. Yagi, 2012. Comparing the technical efficiency of rice farms in urban and rural areas: A case study from Nepal. *Trends Agric. Econ.*, 5: 48-60.
- Potts, M.J. and S. Nagujja, 2012. A Review of Agriculture and Health Policies in Uganda with Implications for the Dissemination of Biofortified Crops. HarvestPlus Working Paper No. 1.
- Reardon, T., 1996. Determinants of Farm Productivity in Africa: A Synthesis of Four Case Studies. SD Publication Series, Africa, pp: 50.
- Sepehrdoust, H., 2011. Housing production and determination of technical efficiency. *Trends Appl. Sci. Res.*, 6: 686-699.
- Soniia, D. and H. Michiel, 1997. Bean Production Systems in Mbale District, Uganda with Emphasis on Varietal Diversity and Adoption of New Climbing Varieties. Network on Bean Research in Africa, CIAT, Occasional Paper Series, Kampala, Uganda.
- Tchale, H., 2009. The efficiency of smallholder agriculture in Malawi. *Afr. J. Agric. Resour. Econ.*, 3: 1-21.
- Tijani, A.A., 2006. Analysis of the technical efficiency of rice farms in Ijesha land of Osun State, Nigeria. *J. Agric. Econ.*, 45: 1-10.
- UBOS, 2010. Uganda National Household Survey 1999/2000: Report on the Crop Survey Module. Uganda Bureau of Statistics, Entebbe.
- Ugwumba, C.O.A., 2010. Allocative efficiency of 'Egusi' Melon (*Colocynthis Citrullus Lanatus*) production inputs in Owerri west local government area of Imo state, Nigeria. *J. Agric. Sci.*, 1(2): 95-100.
- Yao, S. and Z. Liu, 1998. Determinants of grain production and technical efficiency in China. *J. Agric. Econ.*, 49: 171-184.