Efficiency of small scale Pigeon pea production: What do we learn from Malawi?

A. Maganga[1]; G. Grebremedhin[2]; P. Kambewa[1]

1: University of Malawi, Department of Economics, Malawi, 2: University of Bonn, , Germany

Corresponding author email: assamaganga@gmail.com

Abstract:

The study analysed the technical efficiency of small-scale pigeon pea farms in Malawi. 2010/2012 National wide data of 2,137 pigeon pea farmers were analyzed using Maximum Likelihood estimation of a Stochastic frontier. The determinants of technical efficiency were incorporated within single-stage estimation of the frontier. Results revealed that the average output of pigeon pea farms in Malawi could increase by 47% under prevailing technology. The technical efficiency of the sampled pigeon pea farms ranged from 0.22 to 0.84 (0.53 average). Most importantly, the empirical results demonstrate that better extension services and farmer training programs on crop marketing and providing access to credit are key to enhance technical efficiency.

Acknowledegment: Special thanks to World Bank and Malawi National Statistical Office for the data which was made available for this study.

JEL Codes: D22, D24

#1763

Efficiency of small scale Pigeon pea production: What do we learn from Malawi?

Abstract

The study analysed the technical efficiency of small-scale pigeon pea farms in Malawi. 2010/2012 National wide data of 2,137 pigeon pea farmers were analyzed using Maximum Likelihood estimation of a Stochastic frontier. The determinants of technical efficiency were incorporated within single-stage estimation of the frontier. Results revealed that the average output of pigeon pea farms in Malawi could increase by 47% under prevailing technology. The technical efficiency of the sampled pigeon pea farms ranged from 0.22 to 0.84 (0.53 average). Most importantly, the empirical results demonstrate that better extension services and farmer training programs on crop marketing and providing access to credit are key to enhance technical efficiency.

JEL classification codes: D01, D21, O24

Key words: Malawi, Pigeon pea, Technical Efficiency

I. Introduction

A number of dryland legumes adapted to adverse climatic conditions have been developed and released for use by smallholder farmers in the Semi-Arid Tropics as responses to addressing the increasingly harsh climatic conditions (Midega et al., 2015). Such legumes including pigeon pea offer a great opportunity for reversing these trends in productivity, poverty and food insecurity. Pigeon pea is an important legume crop in the production systems of several countries in eastern and southern Africa, primarily in Malawi, Tanzania, Uganda, Kenya and Mozambique (Mligo and Craufurd, 2005; Shiferaw *et al*., 2007). The crop is drought tolerant and grown in most Semi-Arid and drought prone areas in the region. It has a wide range of products, including the dried seed, pods and immature seeds used as green vegetable, leaves and stems used for fodder and the dry stems used as fuel. It also improves soil fertility through nitrogen fixation as well as from the leaf fall and recycling of the nutrients (Mapfumes, 1993; Snapp *et al*., 2002; Rusinamhodzi, 2012). It is an important pulse crop that performs well in poor soils and regions where moisture availability is unreliable or inadequate (Bezner-Kerr et al., 2007; Ngwira et al., 2012). It is also nutritious and cheap source of nitrogen fixing legume that has the potential to enrich soil fertility and is suitable for cash-constrained farmers who cannot afford fertilizer.

Pigeon pea yields grew modestly at an annual growth rate of 1% between 1961 and 2014, although improved varieties were released as early as 1987. The average grain yield of pigeon pea for the period 2001-2006 was about 700 kg/ha (Waldman et al., 2017). This yield is about half of the potential yield on research station of about 1.3 t/ha. The observed yield gap suggests that there is scope for increasing pigeon pea productivity (Nyung'e et al, 2016). The increase in production between 2005 to 2010 made Malawi the top pigeon pea producer in Africa (Nyung'e et al, 2016). The increase in production is possible only through improvement in productivity, which can be increased through on or a combination of factors, namely, technology (i.e. improved varieties), the quantities and types of inputs used and the efficiency with which the resources are used. Of the various determinants, improvement in the technical efficiency of inputs already at the disposal of the farmer is of greater concern (Goyal *et al*., 2006) and widely recognized by researchers and policy makers alike (Arsalanbod, 2005). An underlying axiom behind efficiency estimation is that, if farmers are not making efficient use of the existing technology, their efforts designed to improve technical efficiency would be more cost effective than introducing new technologies as a means of increasing output (Bravo-ureta and Evenson, 1994).

Limited authentic empirical studies have measured farm level technical efficiency in Malawi by using the parametric frontier function (Berre et al., 2017; Chirwa, 2002). However, a survey of the aforementioned literature has revealed that their methodologies did not provide space to test consistency of the production function with what theory says vis-à-vis monotonicity and quasi-concavity. Such treatment of production functions results in inefficiency estimates that cannot be reasonably interpreted especially when dealing with research of policy relevance. In addition, none of these studies have addressed the issue of technical efficiency in pigeon pea production per se.

In designing appropriate policy measures to enable Malawi pigeon pea farms to increase productivity through improved efficiency, it may be useful to measure farm level technical efficiency and its determinants. Therefore, the objectives of this study were (i) to calculate farm level technical efficiency on pigeon pea farms in Malawi (ii) to identify important factors causing efficiency differentials among those farms, and (iii) to infer policy implications based on technical efficiency scores and their determinants.

II. Research Methodology

A. Data Descriptions

This study used nationally representative production data collected by the National Statistical Office through the Third Integrated Household Survey for 2010/11 (NSO, 2012). This survey sampled 12,271 households, of which about 85 percent of households were engaged in agricultural activities. Of these households, about 84 percent of households were engaged in crop production. This agricultural section of the survey was collected by a team of well-trained enumerators. For our analysis, we concentrated on the output and input levels of the pigeon pea production.

Although the survey collected plot level data for each household, the analyses in this study amalgamated pigeon pea plots for each household so as to shift our focus from plot level to household level. The analysis of efficiency in this study is therefore done at the household level. A household is defined as a person or group of persons related or unrelated who live together and make common arrangements for food, or who pool their income for the purpose of purchasing food (NSO, 2012). Three major inputs are used in production of pigeon pea; (i) land, (ii) labor and (iii) seed. Land was measured in hectares and each plot area was verified by data collectors using GPS. Labor was measured in person days devoted to agricultural activities per week based on farmers' recall. Seed was measured in kilograms.

Other variables apart from the pigeon pea output and input levels were the household socioeconomic factors such as household size, the age, sex, marital status and educational level of the household head. Other control variables were the policy and institutional issues such as access to agricultural credit and extension services. We included resource endowment variables including farm size and ownership of treadle pump, radio, bicycle, oxcart and sprayer. We also included spatial variables such as warming, precipitation, distance to nearest ADMARC

(Agricultural Development and Marketing Corporation), market and road and also potential wetness index. The descriptive statistics for all the outputs and inputs are summarized in Table 1.

Table 1: Summary of descriptive statistics of key variables used in the analyses

Variable	Mean/Percent	Std. Dev
Yield (kg)	249.98	36
Land (ha)	0.649	0.64
Labour (person-days)	50.2	56.9
Seed (kgs)	4.32	3.86
Household Size (persons)	4.6	2.05
Age of household head (years)	42.1	16.2
Sex of head (1=Male, 0=Female)	70%	-
Education (none) (%)	79%	-
Primary Education (%)	8.35%	-
Secondary Education (%)	11%	-
Tertially Education (%)	1.65%	-
Married (%)	70%	-
Separated/Divorced (%)	15%	-
Widow (%)	15%	-
Extension on Marketing/crop sales (1=yes,0=no)	6%	-
Extension on Credit (1=yes,0=no)	5%	-
Credit Access (1=yes,0=no)	11%	-
Sprayer (1=yes,0=no)	1.1%	-
Treadle pump (1=yes,0=no)	1.8%	-
Oxcart (1=yes,0=no)	0.2%	-
Radio (1=yes,0=no)	49.1%	-
Bicycle (1=yes,0=no)	43.7%	-
Pigeon pea Intercropped (1=yes, 0=no)	93%	-
Use of organic inputs (1=yes, 0=no)	14%	-
Use of inorganic inputs (1=yes, 0=no)	79%	--
Distance to nearest Road (Km)	1.86	1.35

Distance to nearest ADMARC (Km)	7.58	5.01
Distance to nearest Boma/town (Km)	40.85	2.06
Annual Mean Temperature (Degree Celsius)	22.3	1.13
Annual Mean Precipitation (mm)	1217	261.1
Potential Wetness Index	13.34	2.39

B. Theoretical underpinnings of efficiency modeling

The technical efficiency literature was kick-started by Farrell's (1957) study, which applied the non-parametric frontier approach to measure technical efficiency. To allow for the fact that firms may encounter various uncontrollable exogenous factors (random effects), such as performance of various machines, weather conditions, uncertainty of input supplies, among others Aigner *et al.* (1977) and Meeusen and van den Broeck (1977) developed a stochastic frontier production function. The error term was composite, consisting of random noise and a one-sided residue term.

A number of authors (e.g. Pitt and Lee, 1981; Kalirajan, 1981) have estimated stochastic frontiers to predict firm-level efficiencies, and then regressed the predicted efficiencies upon firm-specific variables such as managerial experience, ownership characteristics and production conditions in an attempt to explain variations in output among firms in an industry. To overcome inconsistencies in the assumptions regarding the independence of inefficiency effects in this two-stage estimation procedure, Kumbha-kar *et al*. (1991) and Reifschneider and Stevenson (1991) propose a single-stage stochastic frontier model in which the inefficiency effects (u_i) are expressed as an explicit function of a vector of firm-specific variables and a random error. This approach is adopted in this study mostly also because of its strength in isolating the effects of exogenous factors from the inefficiency scores. The stochastic frontier production function is expressed as:

(1) $$Yi = f(Xi;\beta)\exp(v_i - u_i) \qquad i = 1,2,3,\ldots,n$$

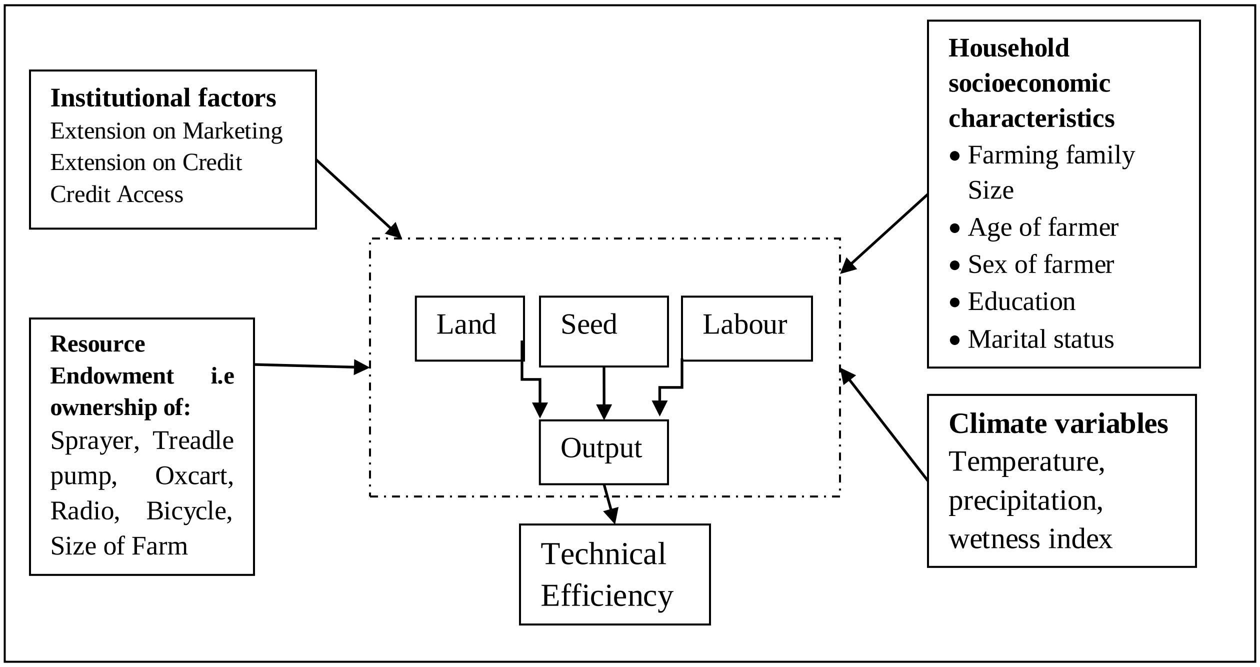
Where, Y_i is the output level for a given farm, X represents a vector of farm inputs entering the pigeon pea production, β is a vector of unknown parameters to be estimated. The first error component, v_i, is the traditional statistical error. The error component, u_i, is a one sided error term (always greater than zero) which defines farmer specific technical efficiency. If it takes on a value of zero it means that the farmer is fully efficient (potential yield is the same as realized yield) and if it takes on other values it denotes inefficiency level with its magnitude given by the magnitude of this error component. From this background we can construct that technical efficiency is given by ratio of actual yield to potential yield:

$$(2) \qquad TE_i = \frac{Y_i}{f(Xi;\beta)\exp(v_i)}$$

TE values ∈ [0, 1], where unity indicates a technically fully efficient farm. Agricultural production is affected by exogenous factors including weather while data analyst of agricultural data faces measurement errors and missing variables. These drawbacks in empirical analysis of technical efficiency can be taken care by use of stochastic frontier methods (Fried et al., 1993; Coelli, 1995; Coelli et al., 1998; Kumbha-kar and Lovell, 2000).

The above background points out that within the immediate production environment, scale of Pigeon pea production is affected by the level of inputs (land, labour and seed). From without the production environment, scale of production among farmer could vary as a result of differences in the household's social economics, institutional, resource endowment, spatial and climate factors (Figure 1)

Figure 1: Conceptual framework for technical efficiency in Pigeon pea production



Source: authors' conceptual framework

C. Empirical Model

Following Fousekis and Klonaris (2003), the empirical application of the frontier is specified in the translog form which: (i) is locally flexible (offers a second-order differential approximation of an arbitrary function); (ii) permits the performance of statistical tests on the structure of the underlying production technology; and (iii) accommodates easily the inclusion of the one-sided error to estimate TE for every observation. The translog frontier function may be written as

$$\text{(3)} \qquad \ln y_i = \alpha + \sum_{k=1}^{3} \beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \beta_{kl} \ln x_{ki} \ln x_{li} + v_i - u_i$$

And, k, l = input 1, …, 3 (i.e. land, seed labor); v denotes the traditional error component and u the non-negative inefficiency component. Error v_i is assumed to be independently and identically distributed, symmetric and independent of $u_{i.}$. Thus the error term $\varepsilon_i = v_i - u_i$ is asymmetric, β_k represents parameters of linear terms, β_{kl} represents parameter of quadratic terms and of interactions. The production function in (3) is assumed to be twice differentiable and symmetry condition is therefore imposed according to $\beta_{kl} = \beta_{lk\ldots}$. Homotheticity and homogeneity of degree 1 is constrained according to $\sum \beta_k = 1$, $\sum\sum \beta_{kl} = 0$. The function determining the technical inefficiency effect is defined in its general form as a linear function of attributes specific to farmers. This is estimated using single stage simultaneously with the Translog production. The inefficient function is specified as:

$$(4) \qquad IE_i = \delta_0 + \sum_{j=1}^{J} \delta_j Z_{ji}$$

Where, Z is a vector of determinants of inefficiency including socioeconomic attributes (i.e. household size, gender, age), education level (none, primary education, secondary education), Marital status (i.e. married, separated, widowed), institutional factors (extension contact, credit access), resource endowment (i.e. sprayer, treadle pump, oxcart, radio, bicycle, farm size), spatial attributes (i.e. distance to nearest road, distance to ADMARC, distance to nearest town, warming, precipitation) and cropping system. The maximum likelihood frontier estimation procedure contained in STATA 14 was applied for the model estimations.

Consistency of the production frontier with microeconomic theory requires that production function be monotonically increasing and quasiconcave in inputs. If a production frontier is not monotonically increasing, the efficiency estimates of the individual firms cannot be reasonably interpreted. Monotonicity means that the output quantity must be non-decreasing, if any input quantity is increased; quasiconcavity guarantees that the marginal rates of technical substitution are decreasing. In the case of our empirical translog production frontier, monotonicity will hold if the following condition suffices:

$$(5) \qquad \frac{dy}{dx_i} = \frac{y}{x_i}\frac{d\ln y}{d\ln x_i} = \frac{y}{x_i}\left(\alpha_i + \sum_{j=1}^{n}\beta_{ij}\ln(x_i)\right) > 0 \, \forall i$$

A sufficient condition for the monotonicity is checked by second order test to verify if the production frontier is decreasing in inputs implying the fulfillment of the following expression:

$$(6) \qquad \frac{d^2 y}{dx_i^2} = \frac{y}{x_i^2} \times \left[\alpha_{ii}\left(\alpha_i - 1 + \sum_{j=1}^{n}\beta_{ij}\ln x_j\right)\left(\alpha_i + \sum_{j=1}^{n}\beta_{ij}\ln x_j\right) + \right] < 0 \, \forall i, j$$

The necessary and sufficient condition for a specific curvature rests in the semi-definiteness of the bordered Hessian matrix. The Hessian matrix is negative semi-definite at every unconstrained local maximum. The conditions of quasi-concavity are related to the fact that this property implies a convex input requirement set (Chambers, 1988). Given our twice continuously differentiable production function, quasi-concavity is checked using its bordered Hessian matrix:

$$(7) \qquad B = \begin{pmatrix} 0 & MP_1 & \cdots & MP_n \\ MP_1 & f_{11} & \cdots & f_{1n} \\ \vdots & \vdots & \ddots & f_{2n} \\ MP_n & f_{n1} & f_{n2} & f_{nn} \end{pmatrix}$$

Where, $f_{ij} = \partial^2 f / (\partial x_i \partial x_j)$ is the second derivative of the production function with respect to the ith and jth input quantities. Since all input quantities are generally non-negative ($x_i \geq 0 \ \forall \ i$), a necessary condition for quasi-concavity is (Chiang, 1984; Takayama, 1994):

$$(8) \qquad |B_1| \leq 0, \quad |B_2| \geq 0, \quad |B_3| \leq 0, \cdots, \quad |B_n| * (-1)^n \geq 0$$

If these theoretical underpinnings (equations ……) are jointly fulfilled the obtained efficiency estimates are consistent with microeconomic theory and consequently can be relied upon to serve as empirical evidence for possible policy measures.

III. Results and Discussions

The most important feature of any econometric estimation is its characteristic to permit researcher to test important hypothesis. The validity of the model estimates depends on the coherence between the estimation procedure and theoretical assumptions. Curvature consistency of the production function was verified firstly by Eigenvalues which were all found to be negative. Secondly, the alternating signs for leading principle minors proved presence of quasiconcavity in production function beginning with a negative first leading principle minor ($|H_1| <0$, $|H_2|>0$, $|H_3|<0$, $|H_4|>0$). Monotonicity in all inputs was satisfied for about 78% of all observations. The theoretical consistency of the estimated production function implies that associated efficiency scores are relevant for the inference of policy measures.

The first hypothesis test was conducted to choose a parsimonious model between Cobb-Douglas and Translog model. If coefficients of the second order and interaction terms in the Translog function are not different from zero, the model collapses to Cobb-Douglas function. We test the null hypothesis: Ho: $\beta_{11} = \beta_{22} = \beta_{33} = \beta_{12} = \beta_{13} = \beta_{23}$ =0, against the alternative that all coefficients of the second order and interaction terms in the Translog function are different from zero. As can be seen below Table 2, the LR chi-square value of is significant at 1 percent. Thus, we reject the null hypothesis at 1% level of significance implying that the Translog functional form adequately captures the crop production behavior of farmers in the study area (Kodde and Palm, 1986).

The second null hypothesis explores that the gamma is zero $(H_0 : \gamma = 0)$, which specifies that the technical inefficiency effects are not present in the model. The estimated value for the variance parameter, γ, in the stochastic production is significant ($p<0.05$), suggesting that inefficiency was present in production and that the traditional "average" production function is not an adequate representation of the data.

Table 1: Maximum likelihood estimates of the Translog Stochastic Production frontier model

Variable	**Parameters**	**Coefficient**	**p-value**
Constant	α	5.286***	
		(0.406)	0.000
Ln(land)	β_1	0.1508***	
		(0.044)	0.000
Ln(labour)	β_2	0.441***	
		(0.167)	0.008
Ln(Seed)	β_3	0.408***	
		(0.163)	0.003
0.5Ln(land) x ln(land)	β_{11}	-0.306***	
		(0.0762)	0.000
0.5Ln(labour) x ln(labour)	β_{22}	-0.105***	
		(0.0420)	0.009
0.5Ln(Seed)xln(Seed)	β_{33}	-0.084	
		(0.0555)	0.129

Variable	Parameters	Coefficient	p-value
Ln(land) x ln(labour)	β_{12}	0.165***	
		(0.0481)	0.001
Ln(land) x ln(Seed)	β_{13}	0.140***	
		(0.0544)	0.010
Ln(Seed) x ln(labour)	β_{23}	-0.056	
		(0.0379)	0.139
Variance Parameters			
Sigma-squared	$\sigma_\varepsilon^2 = \sigma_u^2 + \sigma_v^2$	0.1382***	
		(0.0448)	0.002
Gamma	$\gamma = \sigma_u^2 / \sigma_\varepsilon^2$	0.6157	
		(0.2483)**	0.013
Sigma-squared of *u*	σ_u^2	0.0851	
Sigma-squared of *v*	σ_v^2	0.0530	
Log-likelihood		-31.315	
Observations		2,137	

Ho: $\beta_{11} = \beta_{22} = \beta_{33} = \beta_{12} = \beta_{13} = \beta_{23} = 0$, $\chi^2 = 146$, p-value = 0.000

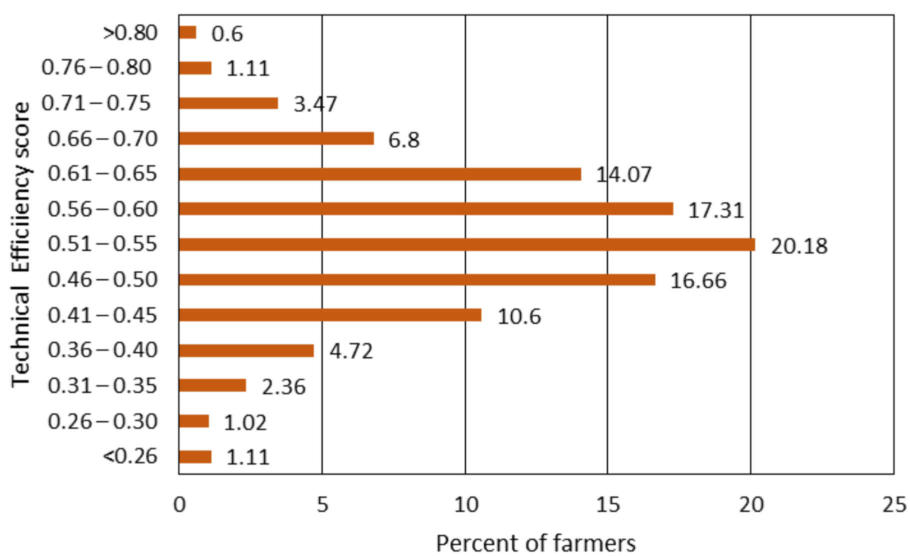
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Thus, technical inefficiency effects have profound impact on pigeon pea yield (Wadud and White, 2000). The estimate of γ indicates that the portion of the one-sided error component in the total variance is as high as 61.57 percent. Thus, 61.57 percent of variation in the data between farms can be attributed to inefficiency and the remaining 38.43 percent is pure due to aspects beyond the farmers' control. The estimated parameter of sigma squared, σ_ε^2, is found to be statistically significant at 1 percent level. This result provides evidence against conventional production function that it may not adequately represent the data.

The above hypothesis tests clearly show that the translog stochastic production frontier is the appropriate model for the given data set and the results are presented in Table 2 above. All the inputs turned out to be positive and significant at less than 1% probability level. Hence, all inputs are very important in the production of pigeon pea production in Malawi.

The estimated and distribution of technical efficiency of pigeon pea production in Malawi are presented in Table 3 below. Research results revealed that the average output of pigeon pea farms in Malawi could increase by 47% under prevailing technology. The technical efficiency of the sample pigeon pea farms ranged from 0.22 to 0.84 (0.53 average). This means that if the average farmer in Malawi were to reach the technical efficiency level of its most efficient counterpart, then the average farmer could experience an increase in production by 36.9% [i.e. (1-(0.53/0.84))x100]. The same computation for the most technically inefficient farmer suggests a gain in production efficiency of 73.9% [i.e. (1- (0.22/0.84)) x 100]. A further analysis showed that those whose scores felled below 0.26 were not economically empowered i.e. endowed with bicycle, radio for agriculture information and had poor access to credit compared to those whose scores were between 41 – 70. However, their land size was relatively bigger.

Table 3: Distribution of Technical Efficiency for Pigeon pea Production



So far, the analysis has focused on the results of the Translog stochastic production frontier of the pigeon pea farms in Malawi. We now turn to the determinants of efficiency of those farms. Variables were mainly categorized into four groups (Socioeconomics, Institutional, Resources endowment and Spatial Variables) were hypothesized to affect efficiency or inefficiency and are presented in Table 4 below. Specific variables from every category were found to be significant affecting efficiency of pigeon pea farms in Malawi suggesting that an all rounded intervention is needed if efficiency in pigeon pea production is going to be boosted in Malawi. To explain drivers of efficiency the determinants equation is used to explain the inefficiency part of the first equation (production frontier), in which case negative parameters would reduce inefficiency (or increase efficiency) and positive parameters would increase inefficiency (or reduce efficiency).

The coefficient of household size is estimated to be positive and statistically significant at less than 1 percent probability level, suggesting that larger families are likely to be technically inefficient. Perhaps, this might be due to the fact that labor allocation for small plot of land of larger families might have caused disguised unemployment which increases the actual cost of production. As expected, our results show that education has a positive effect on efficiency or it is negatively related with inefficiency. Primary education and secondary education were positive and significant at less than 10% and 1% probability level, respectively. This manifests the importance of human capital in efficient production of farms.

One of the resource endowment variables that were hypothesized to affect efficiency of pigeon pea was ownership of bicycle. Ownership of bicycle has a positive effect on efficiency of production being significant at less than 5% probability level. This is due to the fact that, bicycle is used as a tool for transporting inputs and outputs from and to market in the Malawi context. The other resource endowment variable which turned out to be significant was farm size. The variable had a negative and significant effect on efficiency ($p < 0.01$). The result was unexpected; however, there are probable logical explanations about it. One possible explanation is that, households who have small plots are expected to manage their land efficiently so that they sustain their family. This finding corroborates that by (Schultz, 1964; Lau and Yotopoulos, 1971; Sidhu, 1974; Huang and Bagi, 1984; Squires and Tabor, 1991). Different researchers have had conflicting findings on the relationship between farm size and efficiency. Some authors have found that efficiency level was irrespective of farm size (Torkamani and Hardaker, 1996; Laura Gow and Langemeier, 1999. However, still others have found a positive size-efficiency relationship (Pinherio, 1992; Curtis, 2000; Latruffe *et al.*, 2002).

Table 4: Determinants of Technical inefficiency in Pigeon pea Production

Variable	Coefficient	Std. Err	p-value
Socioeconomics			
Household Size	0.0434***	0.0113	0.000
Age of household head	-0.0277	0.0182	0.127
Age Squared	0.0191	0.0135	0.156
Gender of head	-0.0586	0.0875	0.505
Education (None)	0.0419	0.0268	0.118
Primary Education	-0.0482*	0.0276	0.080
Secondary Education	-0.3821***	0.0274	0.163
Married	-0.0297	0.0196	0.130
Separated/Divorced	0.0236	0.0202	0.244
Widow	0.0233	0.0208	0.262
Institutional			
Extension on Marketing/crop sales	-0.1390***	0.0141	0.000
Extension on Credit	-0.0497	0.103	0.244
Credit Access	-0.288**	0.121	0.018
Resource Endowment			
Sprayer	0.0175	0.0191	0.360
Treadle pump	-0.00621	0.0146	0.671
Oxcart	0.0909	0.2832	0.712
Radio	-0.0909	0.0851	0.242
Bicycle	-0.100**	0.0459	0.029
Size of Farm	0.0623***	0.00385	0.000
Spatial Variables			
Distance to nearest Road	0.1982	0.1572	0.208
Distance to nearest ADMARC	0.0477	0.0416	0.251
Distance to nearest Boma/town	0.0465***	0.0104	0.000
Climate variables			
Annual Mean Temperature	0.0548**	0.0241	0.023

Annual Mean Precipitation	0.0467***	0.0103	0.000
Farming system			
Mixed cropping	-0.0492	0.0812	0.544
Organic fertilizer	-0.0650	0.0368	0.078
Inorganic fertilizer	-0.0509	0.0307	0.097
Constant	-0.4476***	0.087	0.000
Observations	2,137		

*** p<0.01, ** p<0.05, * p<0.1

It was hypothesized that farms with an access to extension on credit and credit itself would operate closer to the frontier. The coefficient of this variable shows the expected and statistically significant result at 1 percent probability level implying that credit use played important role in efficiency of production. Credit access is very important in agricultural production. It enables farmers to purchase farm inputs during the production period which is characterised by very little cash revenue, while expenditures on inputs and consumption must be born.

Cash revenue comes in just after harvest. Credit use therefore increased technical efficiency, a result similar to the findings of Binam *et al*. (2004) and Zavela *et al*. (2005). Similarly, extension service on marketing and crop sales enhanced technical efficiency of farms. With knowledge of crop sales and marketing, farmers become profit oriented, consequently, they make sure that they increase productivity of the limited resources at their disposal.

This study also included some spatial and climate variables as the determinants of efficiency differentials in Malawi. Among the spatial variables that turned out to be significant was distance to nearest town and was negatively related with technical efficiency at less than 1 percent probability level. This indicates that farm households that were near towns are more technically inefficient on pigeon pea production than those who reside far. This could be due to the fact that, those farm households closer to town have a high probability of engaging in nonfarm activities and spent less time on their farms than those who reside far and hence less efficiency. With regard to climate variables, temperature and rainfall varies both across regions, districts and within districts, hence using the actual climate variables would increase precision of estimates.

The study has revealed a negative and significant relationship between mean annual temperature and technical efficiency of farm households in pigeon pea production in Malawi at less than 1 percent probability level. This implies that, as environment becomes warmer technical efficiency decreases. Furthermore, precipitation significantly and negatively affected technical efficiency. Thus, pigeon pea production will not benefit from climate change that is caused by increases in warming and precipitation.

With regard to cropping system, pigeon pea is dominated by intercrop as observed in 93% of the sample farmers. Intercrop did not affect the level of technical efficiency ($p > 0.1$). The predominance of intercropping meant that pigeon pea benefited from both organic and inorganic fertilizer from applied on the same plot for the intercrops. These two were found to boost technical efficiency in pigeon pea though marginally with latter.

IV. Conclusions

A stochastic frontier approach was employed to set out the level of technical efficiency and simultaneously determine the farm specific factors that affect level of efficiency of pigeon pea farms in Malawi. A survey was carried out to collect cross sectional data in 2010 production season. The Stochastic frontier production function was estimated using maximum likelihood to obtain asymptotically efficient and consistent parameter estimates and determinants of inefficiency. The diagnostic checks confirmed the relevance of stochastic function, presence of one sided error component, and that a classical regression model of production based on ordinary least square estimation would be inadequate representation of the data for analysis of pigeon pea technical efficiency in Malawi.

The empirical findings also revealed that 61.57 percent of the variation in pigeon pea output from the frontier is due to technical inefficiency. The technical efficiency scores of the pigeon pea farms ranged between 22 to 84 percent with a mean value of 53 percent. Hence, the average output of pigeon pea farms in Malawi could increase by 47 percent under prevailing technology. A close examination of the relationship between technical efficiency and the various factors that are assumed to determine efficiency indicated that household size, farm size, distance to nearest market, temperature and precipitation negatively affected technical efficiency. However, education, crop marketing extension service, credit access and bicycle ownership showed a positive relationship with efficiency. Therefore, this study proposes strategies such as providing better extension services and farmer training programs on crop marketing, raising the educational level of farmers, and providing farmers with greater access to credit, to enhance technical efficiency. Further, study can be done to explore technical efficiency differential among different varieties of pigeon pea.

Reference

Aigner, D.J. Lovell, C.A.K. and Schmidt, P. (1977), Formulation and estimation of stochastic frontier production function models, *Journal of Econometrics* **6**(1): 21-37.

Midega, C.A.O., Toby J.A.Bruce. T.J.A., Pickett, J.A., Pittchar, J.O., Murage, A.,Khan, Z.R., (2015). Climate-adapted companion cropping increases agricultural productivity in East Africa. Field Crops Research, Volume 180, Pp 118-125. doi.org/10.1016/j.fcr.2015.05.022.

Mligo, J.K., and Craufurd, P.Q (2005). Adaptation and yield of Pigeon pea in different environments in Tanzania. Field Crops Research, Volume 94, Issue 1, Pp 43-53. https://doi.org/10.1016/j.fcr.2004.11.009.

Rusinamhodzi, L., Corbeels, M., Nyamangara, J., Giller, K.E. (2012). Maize–grain legume intercropping is an attractive option for ecological intensification that reduces climatic risk for smallholder farmers in central Mozambique**.** Field Crops Research, Volume 136, 20 September 2012, Pages 12-22. https://doi.org/10.1016/j.fcr.2012.07.014

Ngwira A.R., Aune, J.B., Mkwinda, S. (2012). On-farm evaluation of yield and economic benefit of short term maize legume intercropping systems under conservation agriculture in Malawi. Field Crops Research, Volume 132, Pp 149-157. doi.org/10.1016/j.fcr.2011.12.014

Waldman, K.B., Ortega, D.L., Richardson, R.B., Snapp, S.S. (2017). Estimating demand for perennial pigeon pea in Malawi using choice experiments. Volume 131, Pages 222-230. doi.org/10.1016/j.ecolecon.2016.09.006

Njung'e, V., Deshpande, S., Siambi, M., Jones, R., Silim, S., Villiers, S. (2016). SSR genetic diversity assessment of popular Pigeon pea varieties in Malawi reveals unique fingerprints. *Electronic Journal of Biotechnology*. Volume 21, May 2016, Pages 65-71. doi.org/10.1016/j.ejbt.2016.02.004.

Berre D., Corbeels, M., Rusinamhodzi, L., Mutenje, M., Thierfelder, C., Lopez-Ridaura, S. (2017). Thinking beyond agronomic yield gap: Smallholder farm efficiency under contrasted livelihood strategies in Malawi. Field Crops Research, Volume 214, December 2017, Pages 113-122, doi.org/10.1016/j.fcr.2017.08.026.

Arsalanbod, M. (2005), The efficiency of farmers in north west of Iran, *Indian Journal of Agricultural Economics* **60**(1): 101 – 109.

Binam, J.N., Tonye, J., Wandji, N., Nyambi, G., and Akoa, M., (2004), Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon, *Food Policy* **29**: 531– 545.

Bravo-ureta, B.E. and Evenson, R.E., (1994), Efficiency in agricultural production: the case of peasant farmers in Eastern Paraguay, *Agricultural Economics* **10** (1): 27 – 28.

Bravo-Ureta, B.E., and Pinheiro, A.E. (1997), Technical, economic and allocative efficiency in peasant farming: evidence from the Dominican Republic, *Development Economics* **35**: 48–67.

Chambers, R. (1988), *Applied production analysis: a dual approach*, Cambridge, Cambridge University Press.

Chiang, A.C. (1984), *Fundamental methods of mathematical economics*, 3rd Ed., McGraw-Hill.

Chirwa, E.W. (2002), Sources of technical efficiency among smallholder maize farmers in Southern Malawi. *Work in progress report presented at the biannual research workshop organised by the African Economic Research Consortium*, Durban, South Africa, December.

Coelli, T.J. Rao, D.S.P. and Battese, G.E. (1998), *An introduction to efficiency and productivity analysis*, Kluwer Academic Publishers, Boston, Dordrecht/London, P, 134 - 249.

Coelli, T.J., (1995), Estimators and hypothesis tests for a stochastic frontier function: a Monte Carlo analysis. *Journal of Productivity Analysis* **6**: 247–268.

Curtis, J., (2000), Technical efficiency and competitiveness of the Czech agricultural sector in late transition-the case of crop production. *Paper presented at the KATO Symposium*, November 2000: 2–4, Berlin.

Farell, M.J. (1957). The measurement of production efficiency, *Journal of Royal Statistical Society, Series A*. (General), Part 3, **120**: 253-290.

Fousekis, P., and Klonaris, S. (2003). Technical efficiency determinants for fisheries: a study of Trammel Netters in Greece, *Fisheries Research* **63**: 85–95.

Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (1993), *The measurement of productive efficiency: techniques and applications*, Oxford University Press, New York.

Goyal, S.K., Suhag, K.S., and Pandey, U.K. (2006), An estimation of technical efficiency of paddy farmers in Haryana State of India, *Indian Journal of Agricultural Economics*, **61**(1): 108 – 122.

Hjalmarsson L., Kumbhakar S. and Hesmati A. (1996), DEA, DFA and SFA: A comparison, *Journal of Productivity Analysis* **7**: 303-327.

Huang, C.J., and Bagi, F.S., (1984). Technical efficiency on individual farms in Northwest India, *Southern Economic Journal* **51**, 108–115.

Kalirajan, K. (1981). An econometric analysis of yield variability in paddy production, *Canadian Journal of Agricultural Economics* **29**: 283– 294.

Kodde, D. A., and Palm, F.C. (1986). Wald criteria for jointly testing equality and inequality restrictions. *Econometrica* **54**(5): 1243-1248.

Kopp, R.J. and Diewert, E. (1982), The decomposition of frontier cost function deviations into measures of technical and allocative efficiency. *Journal of Econometrics*, **19**: 319 – 331.

Kumbhakar, S.C., and Lovell, C.A.K. (2000). *Stochastic frontier analysis*, Cambridge, Cambridge University Press.

Kumbhakar, S.C., Ghosh, S., McGuckin, J.T., (1991). A generalized production frontier approach for estimating determinants of inefficiency in U.S. dairy farms, *Journal of Business and Economic Statistics* **9**: 279–286.

Latruffe, L., Balcombe, K., Davidova, S., Zawalinski, K., (2002), Determinants of technical efficiency of crop and livestock farms in Poland. Working paper 02-05, Institut National de la Recherche Agranomique, France.

Lau, L.J., Yotopoulos, P.A., (1971). A test of relative efficiency and application to Indian Agriculture. *American Economic Review* **61**: 94–109.

Laura Gow, M.S., Langemeier, M., (1999), An efficiency analysis of cattle backgrounding in Kansas: Paper presented at Western Agricultural Economics Association Annual Meeting, Fargo, ND. 11–14 July.

Mapfumes P. (1993). Pigeon pea in Zimbabwe: A new crop with potential in soil fertility research for maize based farming systems in Malawi and Zimbabwe. International Pigeon pea Newsletter, (7):12

Meeusen, N., Van, D., Broeck, J. (1977), Efficiency estimation from Cobb-Douglas production function with composite error, *International Economic Review* **18**(2): 123 -134.

Pinherio, A., (1992), An econometric analysis of farm level efficiency of small farms in Dominican Republic, Unpublished MSc Thesis, University of Connecticut, Storrs.

Pitt, M.M., Lee, M.F. (1981), Measurement and sources of technical inefficiency viewpoint in the Indonesian weaving industry, *Journal of Development Economics* **9**: 43– 64.

Reifschneider, D., and Stevenson, R., (1991), Systematic departures from the frontier: a framework for the analysis of firm inefficiency, *International Economic Review* **32**: 715–723.

Schultz, T.W., (1964), *Transforming traditional agriculture*. Yale University Press, New Haven, CT.

Sharma K.R., Leung P. and Zalenski H.M. (1997), Productive efficiency of the swine industry in Hawai: stochastic frontier vs. data envelopment analysis, *Journal of Productivity Analysis* **8**: 447-459.

Shiferaw, B, Jones R, Silim S, Tekelewold H and Gwata E. (2007) Analysis of production costs, market opportunities and competitiveness of desi and kabuli chickpea in Ethiopia. IMPS(Improving productivity and market Success) of Ethiopian Farmers Project Working Paper 3. ILRI (International Livestock Research Institute), Nairobi, Kenya. 48pp.

Sidhu, S.S., (1974), Relative efficiency in wheat production in the Indian Punjab, *American Economic Review* **64**: 740–751.

Snapp S. S., Rohrbach D. D., Simtowe F., Freeman H. A. (2002). Sustainable soil management options for Malawi: can smallholder farmers grow more legumes? *Agric. Ecosyst. Environ.* 91 159–174

Squires, D., and Tabor, S., (1991), Technical efficiency and future production gains in Indonesian agriculture, *The Developing Economies* **29**: 258–270.

Takayama, A. (1994). *Analytical methods in economics*, Harvester Wheatsheaf.

Torkamani, J., and Hardaker, J.B., (1996). A study of economic efficiency of Iranian farmers in the Ramjerd district: an application of stochastic programming, *Journal of Agricultural Economics* **14**: 73–83.

Wadud A. and White B. (2000), Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods, *Applied Economics* **32**: 1665-1673.

Zavela, H., Mabaya, E., Christy, R. (2005), Smallholders' cost efficiency in Mozambique: Implications for Improved Maize Seed Adoption. Staff paper, SP-2005-04, Department of Applied Economics and Management, Cornell University, New York, USA.