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Farm Household Production Efficiency in Southern Malawi: An Efficiency Decomposition Approach

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Abstract
The present study was set out to estimate production efficiency of tomato (*Lycopersicon esculentum* L) farmers in the southern region of Malawi's through efficiency decomposition. A random sample of 72 small-scale farmers was drawn from Balaka district. The findings revealed that farmers in Balaka district have opportunity for productivity gains and cost saving. Mean technical, economic and allocated efficiency were found to be 0.70, 0.57 and 0.82, respectively. Factors like education and credit access augment technical efficiency while credit access, farmer group membership and gender (being male) augment economic and allocative efficiency. Policy thrust like linking small scale farmers to micro-finance institutions for credit access, intensifying family planning programs to reduce family sizes, organizing small scale farmers into groups (cooperatives) and integrating women into training and extension programs would increase production efficiency of small-scale tomato farming in southern Malawi.

Keywords: Decomposition, Malawi, production efficiency, production frontier, tomato

INTRODUCTION

During the 2000s, Malawi's agriculture accounted for as much as 35-40 percent of the Gross Domestic Product (GDP), 92 percent of overall employment, over 90 percent of the country's foreign exchange earnings, provided 64% of total income for rural people and contributed 33.6 percent to the economic growth. Agriculture supports the manufacturing industry by supplying 65% of the raw materials needed. A significant feature of the Malawi's agriculture is dualism in its structure. This dual structure consists of large scale farming, which includes estates sector, and small scale production (GoM, 2007 and Damaliphetsa et al., 2007).

There has been, however, over-dependence on tobacco and maize for foreign exchange earnings and the provision of food, respectively. Tobacco accounts for over 70% percent of the export earnings whereas maize occupies over 70% of the cropped land area. Both crops, however, face strong turbulence, tobacco from the anti-smoking lobby and maize from the escalating costs of inputs (Chongwe, 2001). These are not just threatening the survival of these crops, but the very foundation of Malawi's economy. Thus, alternative enterprises must be borne to take lead in agriculture, and it goes with mention that horticultural crops may offer the best avenue.

One horticultural crop gaining much interest in Malawi is tomato (*Lycopersicon esculentum* L). In Malawi, tomato is used as food item on daily basis. It can be considered as the most prevalent of all vegetables. It is mostly used as fresh vegetable and can also be used for making a vector of products as well. Declining foreign exchanges reserves would be rescued by reduction in importation of tomato products which can locally be produced i.e tomato sauce. This will first require an assignment to analyze possible productivity gains in tomato production given increasing population growth (NSO, 2008) or demand and fixed land resource. This study rolled out to undertake such an assignment mainly looking at efficiency.

To the knowledge of the authors, no research has been done on productivity gains in horticulture sector later isolating tomato crop. It appears the first wave of research focused on big crops like maize and groundnuts (Edriss and Simtowe, 2002; Tchale, 2009). Maganga (2012) rolls another strand of research on productivity gains in horticultural crops, but only focus on Irish potato. Despite this expanding body of literature on efficiency, no study has specifically focused on production efficiency in tomato farming. Thus, the first objective of this study is to estimate production efficiency of tomato farming in the southern Malawi. In order to provide policy implications, the efficiency measurements will be decomposed into technical, allocative and economic efficiencies using stochastic efficiency decomposition production frontier analysis.

Finally, the study attempts to explore relationship between the production efficiency measures and other relevant variables such as education, household size, land size, access to credit, membership to farmer organization and gender. It is essential to identify the sources of production efficiency in order to design private or public policies to improve performance (Lovell, 1995).

METHODOLOGY

Theoretical Construct

Production function is defined by Ferguson (1966) as a function that relates maximum possible output to a given combination of inputs. An output function estimated by Ordinary Least Squares represents an average response and does not in a sense represent a production frontier. The frontier and technical efficiency literature dates back as early as (1957) by Farrel's work in his estimation of technical efficiency using deterministic frontier. This approach overlooked random factors beyond the farmer's control that can affect the efficiency of a farm. Consequently, the approach went through some refinements by Aigner et al. (1977) and Meeusem and Broeck (1977) when they employed cross-sectional data to estimate technical efficiency using a stochastic frontier model. The stochastic element was hypothesized to be composite comprising of a half normal random error component and one sided residual term. The first accounts for measurement errors in output variable, weather and a combined effect of unknown inputs on production.

A further departure from deterministic approach in the body of literature includes Timmer (1971), Ferrier and Lovell (1990), Fosund (1992) and others. These papers show a switching from deterministic frontier into a probabilistic frontier function. The present study follows Timmer (1971), Ferrier and Lovell (1990), Fosund (1992) and adapts to efficiency decomposition methodology firstly presented by Kopp and Diewert (1982) and extended by Bravo-Ureta and Riegner (1991). The production technology of a farm is represented by a stochastic production function specified as:

1 $$Y_i = f(X_i;\beta) + v_i - u_i$$

Where Y_i denotes the tomato output for farm i, X is the vector of inputs or functions of input quantities used by i^{th} farm, β is a vector of parameters to be estimated, $f(X_i;\beta)$ is a true representation of tomato production function, v_i is the traditional stochastic error term, the u_i*s* are non-negative random variables associated with technical inefficiency in production, which are assumed to be independently and identically distributed, $N(0,\sigma_u^2)$ and truncated at zero, of the normal distribution with mean μ and variance $\sigma_u^2(|N(\mu,\sigma_u^2|)$.

The maximum likelihood estimates yield β, $\sigma^2=\sigma_v^2+\sigma_u^2$ and $\gamma=\sigma_u^2/\sigma^2$. Following Jondrow *et al*. (1982), the technical efficiency estimation is given by the mean of the conditional distribution of inefficiency term μ_i given ε; and thus defined by:

2 $$E(u_i|\varepsilon_i)=\frac{\sigma_v-\sigma_u}{\sigma}.\left[\frac{f(\varepsilon_j\lambda|\sigma)}{1-F(\varepsilon_i\lambda|\sigma}-\frac{\varepsilon_i\lambda}{\sigma}\right]$$

Here, λ = $\sigma_v/\sigma_u, \sigma^2=\sigma_v^2+\sigma_u^2$ while f and F represents the standard normal density and cumulative distribution function, respectively, evaluated at $\varepsilon_i\lambda/\sigma$. Removing the inefficiency component from equation 1 yields

3 $$Y^*=Y_i-u_i=f(X_i;\beta)-u_i$$

Where Y^* is the observed tomato output of the *ith* farmer adjusted for the stochastic noise v_i (Bravo-Ureta and Rieger, 1991). This forms a starting point for deriving a technically efficient input vector, X_i^t, for ith farm. The technically efficient input vector is derived by simultaneously solving observed output, equation 4 and the input ratios ($X_1/X_i = k$ $(i>1)$), where k is the observed input ratio.

Given that equation 1 is Cobb-Douglass production function, it is assumed that it is self dual. Thus, the dual cost frontier can be derived algebraically having the general form specified as:

4 $$C_i=\tau(W_i,Y^*;\varphi)$$

This represents the minimum cost associated with tomato production, W_k is the input price vector for *ith* farm and φ is a vector of parameters to be estimated. The economically efficient input vector X_k^e is found by applying Shephard's lemma and substituting firm's input prices and adjusted output level Y^* into the resulting level of input demands yields

5 $$\frac{\partial C}{\partial W_k}=X_k^e(W_{ki},Y_i^*;\phi)$$

Where, k ranges from 1 to m inputs, ϕ is parameter vector to be estimated. With observed level of output, the technically and economically efficient costs of production are equal to $W_i'X_i^t$ and $W_i'X_i^e$, respectively. While the actual operating input cost of the farm is $W_i'X_i$. The three cost measures can then be used to compute the technical (TE) and economic efficiency (EE) indices as follows;

6 $$TE = \frac{W_i'X_i^t}{W_i'X_i}$$

7 $$EE = \frac{W_i'X_i^e}{W_i'X_i}$$

The combinations of equations (6) and (7) is used to obtain the allocative efficiency (AE) index following Farell (1957) as

8 $$AE = \frac{W_i'X_i^e}{W_i'X_i^t}$$

Economic efficiency of i^{th} farm ($W_i'X_i$ - $W_i'X_i^e$) can be decomposed into its technical ($W_i'X_i$ - $W_i'X_i^t$) and allocative ($W_i'X_i^t$ - $W_i'X_i^e$) components.

Empirical Model

Setting out to analyze technical, economic and allocative efficiencies, the following production function was estimated;

9 $\ln Y_i = \beta_0 + \beta_1(LAND) + \beta_2(LABOUR) + \beta_3(FERT) + \beta_1(SEED) + (v_i - u_i)$

Where, Y is tomato output in kg, *LAND* is total land size in hectares committed to tomato production, *LABOUR* is used in a production season measured in man-days, *FERT* is inorganic fertilizer applied to tomato in kgs, *SEED* is the quantity of seed in number of seed packets, and β, v_i and u_i are as defined earlier.

The cost minimizing problem in equation 10 is the basis for deriving the dual cost frontier, given the input prices W_k, parameter estimates of the stochastic frontier production function, $\hat{\beta}_k$ and adjusted output level, Y_i^*.

10 $$\min C = \sum_{k=1}^{4} W_k X_k$$

11 Subject to $$Y_i^* = \hat{A}\prod_k X_k^{\hat{\beta}_k}$$

Where $\hat{A} = \exp(\hat{\beta}_o)$. Substitution of the cost minimizing input quantities yields the following dual cost function:

$$12 \quad C(Y^*, W) = \psi Y^{*\mu} \prod_{k=1}^{4} W_k^{\alpha_k}$$

Where, $\alpha_k = \mu \hat{\beta}_k$, $\mu = (\sum_k \hat{\beta}_k)^{-1}$,

The input prices, W_k, are averages of observed prices per unit of the inputs used.

Discovering whether farms are efficient might not be important exercises unless an additional effort is made to identify the sources of the inefficiencies. Taking cognizance of this, the study investigated the sources of plot-level inefficiencies for the surveyed farmers. Empirically, the inefficiency model u_i is specified as;

$$13 \quad u_i = \varpi_0 + \sum_{r=1}^{9} \varpi_r z_{ri}$$

Where, z_r is a vector of farm specific determinants of economic inefficiency, ϖ is a vector of inefficiency parameters to be estimated.

Data

This study used the cross-sectional household survey data from Malawi collected during the 2009/2010 cropping season from a random sample of 72 tomato producers in Balaka district in southern Malawi. Household level data were validated using Focus Group Discussions in the sampled communities. Balaka district covers an area of 2,193 km² (BDA, 2003).

Results and Discussion

A basic summary of the values of the key variables used in this study is presented in Table1. An average farmer showed that they had 15 years of farming, 4 years of formal education and were 39 years of age. Tomato production was dominated by male farmers (77%). The figures are on per farm basis. The average tomato productivity per farm was 19t/ha. The area under tomato for the sampled farmers varied from a very small farm of 0.2ha to a large farm of 2 ha. Labour use was low with a mean value of 15 person-days. The average number of seedlings planted per hectare was 17824. Credit access is very low in the area. Only 34% of farmers had access to credit. This could perhaps be attributed to low levels of farmer group memberships. Farmer group membership was as low as 33%.

The maximum-likelihood estimates of the parameters in the Cobb-Douglass stochastic frontier production function are presented in Table 2. The parameters for land, labour, fertilizer and seed were positive and significant as expected. In addition, the Wald chi-square statistic for joint test of the model indicates that the model is significant ($p < 0.01$), overly. The estimated values for the variance parameters were significant and indicated that technical efficiency had an impact on the total value of tomato production. The gamma ($\gamma = 0.93$) shows that 93% of the variability in the output of tomato farmers that are unexplained by the function is due to economic inefficiency. This suggested that a conventional production function was not an adequate representation of the data.

The dual cost frontier of equation 14 is derived from maximum-likelihood estimates of frontier production function for Table 2 yielding:

(14) $\ln C = 13.48 + 0.2343\ln W_1 + 0.3468\ln W_2 + 0.3159\ln W_3 + 0.0661\ln W_4 + 0.9814Y^*$

Where, C is the production cost of tomato, W_1, W_2, W_3 and W_4 are land rent, wage rate, fertilizer cost and seed cost, respectively, adjusted for any statistical noise.

Efficiency Scores

The frequency distribution of technical, economic, and allocative efficiency estimates were summarized and presented in Figure 1. The technical efficiency estimates range from 0.41 to 0.98 with a mean of 0.70 implying that the farmers have liberal opportunities to increase their technical efficiency. The result indicates that the most technically inefficient farmer would have an efficiency gain of 58.16 percent derived from (10.41/0.98)×100 to attain the level of the most technically efficient farmer.

The economic efficiency estimates range from 0.27 to 0.86 with a mean of 0.57 implying that the farmers have sufficient opportunities to increase their economic efficiency. The result indicates that the average tomato farmer would enjoy a cost saving of about 33.72 percent derived from (1 - 0.57/0.0.86)×100 to attain the level of the most efficient farmer. The allocative efficiency ranged from 0.49 to as high as 0.98 while having a mean of 0.82. The result indicates that an average tomato farmer would enjoy a cost saving of about 21.21 percent derived from (1 - 0.78/0.99)×100 to attain the level of the most efficient farmer.

Sources of Efficiency Gains

The major interest behind measuring technical efficiency level is to know what factors determine the efficiency level of individual farmers. Various hypothesized variables that are expected to determine efficiency differences among farmers were estimated using equation 13. The results are presents in Table 3.

Education is a variable that is expected to sharpen managerial input and lead to a better assessment of the importance, and complexities, of good decisions in farming. Education enhances the ability of farmers to see, decode and make good use of information about production inputs, thus improving the efficiency in input use. The coefficient of years of exposure to education had negative estimated coefficient that were significantly different from 0 ($p<0.1$) for technical efficiency and positive estimated coefficient that were significantly different from 0 ($p<0.05$) for allocative efficiency. Farmers' education increased technical efficiency of the tomato farmers. Earlier studies by Awudu, *et al*., (2001) and Abdulai and Eberlin (2001) in their studies on technical efficiency in Nicaragua established that education increased production efficiency. Farmers' economic efficiency was neutral to education level.

Family labor constitutes the major labor supply to the farm. The size of economically active family members within a given farming household affects the crop production activities. Thus, a large family size would manage crop plots on time. The study reported positive relationship between family size and technical and allocative efficiency though not conventionally significant. However, it showed negative relationship with economic efficiency for which the impact was significant ($p<0.01$) on the latter.

In this study, farmer experience was accumulated number of years in tomato production which builds along with it skills and abilities. With experience, the farm manager is able to evade previous flows, and identify the right mix of inputs to maximize output and profits. To the contrary, this study reported opposite relationship between farmers' farm experience and technical and economic efficiency. However, farm experience only had significant effect on technical ($p<0.05$) and economic ($p<0.1$) efficiencies. The result does not corroborate that of Onyenweaku and Nwaru (2005), Onyenweaku, *et al.* (2004) and Kalirajan (1981). Onyenweaku and Okoye (2007) notes that more experienced a farmer is the more efficient his decision making processes and the more he will be willing to take risks associated with the adoption of innovations.

Land size is expected to increase production efficiency through increased scale economies. However, the present study found an inverse and significant ($p<0.01$) between technical efficiency and land size (small is beautiful). Similarly, Bagi (1982) estimated a Cobb-Douglas production function for three groups of Indian farms, including a size dummy (based on land) both additively and interactively with the rest of the inputs. He found that, given a level of inputs, small farms produced more output than large farms

Access to credit can be an important source of farm business financing in developing agricultural economies. Higher access to credit, in this study, increased technical, allocative, and economic efficiency positively ($p<0.01$). In previous studies, Okike et al. (2001) found positive relationship between economic efficiency and credit access. The beauty of access to credit lies in outward shifting of the farm budget constraint, enabling timely purchase of inputs, if it is accessed on time. Membership to farmer organization helps to reduce production costs as farmers may use the opportunity of purchasing inputs in bulk. The variable positively determined economic and allocative efficiency and were significant ($p<0.5$). Similarly, gender of the farmer only increased economic and allocative efficiency ($p<0.01$).

CONCLUSION AND POLICY IMPLICATIONS

This study derived the production (technical, economic and allocative) efficiency indices for tomato farms in the Balaka district of Malawi by using efficiency decomposition from Cobb Douglas production frontier. The mean technical, economic and allocative efficiencies of farms were 0.70, 0.57 and 0.82, respectively, indicating that there are opportunities to gain substantial additional output or decrease inputs, given the existing technology of tomato farmers in the research area.

Farm level explanatory variables were used to explore inefficiency determinants. The inefficiency effect model showed that factors such as education and access to credit augmented technical efficiency while farming experience, land size showed a negative relationship with technical efficiency. Economic efficiency was positively affected by household size, access to credit, farmer groups and gender while being undermined by farm experience. Allocative efficiency was directly related to credit, farmer groups and gender (being male).

Based on the results, the authors of this study propose strategies such as linking farmer to micro-finance institutions for credit, intensify family planning programs to reduce family sizes, organize farmers into groups (cooperatives), integrating women into the training and extension programs in order to increase the production efficiency of tomato farms in the Balaka district.

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Table 1: Definition of variables and descriptive statistics

Variable	Units	Average	Minimum	Maximum
Age	Years	39	18	76
Education	Years	4	1	8
Farming Experience	Years	15.3	1	50
Land size	Hectares	0.2	0.8	2
Land rent	Imputed cost of land	3329	2952	3538
Extension visit	No. of visits	1	0	12
Fertilizer	Kg/ha	130	75	150
Price of fertilizer	Malawi kwacha/kg	22	15	30
Labour	Person-days/ha/year	15.17	5	275
Wage rate	Price of labour/month	2500	1200	3500
Tomato yield	t/ha	19	12	30
Tomato price	Malawi kwacha/kg	150	145	200
Household size	No of persons	5	1	13
Seed price	Malawi Kwacha/packet	150	150	150
Seed quantity	Seedlings/ha	17824	16343	17978
Gender of household head	1=Male; 0 =otherwise	0.77	0	1
Hoes	Number of hoes	4	1	8
Cost of hoes	Total cost of hoes	1067	100	3200
Credit status	1=access 0 = otherwise	0.34	0	1
Farmer organization membership	1=yes; 0 = Otherwise	0.33	0	1

1. 1USD = 150 Malawi Kwacha (MK)

Table 2: Maximum Likelihood Stochastic Production Frontier Output

Variable	Coefficient	Std. Error	p> |z|
Ln(LAND)	0.238807	0.0001554	0.000
Ln(LABOUR)	0.353326	0.0000569	0.000
Ln(FERT)	0.321928	0.0000597	0.000
Ln(SEED)	0.067401	0.0000236	0.000
Constant	7.277318	0.0000794	0.000
Total variance (σ^2)	0.234	0.057	0.023
Variance ratio (λ)	0.93	0.231	0.000
Log-likelihood function	-76.11		
Wald chi2(4)	3.67		0.000

Source: Computed from STATA 11 MLE/Survey data, 2010. *, ** and *** = Significant at 10%, 5% and 1% respectively

Table 3: Inefficiency Effects Determinants

	Inefficiency coefficient		
Variable	**Technical**	**Economic**	**Allocative**
Education level	- 0.828(-1.67)*	-0.021(-0.851)	2.108 (0.679)**
Household size	-0.0529(0.041)	0.292(0.105)***	-0.003(0.007)
Farming experience	0.1359(0.012)**	0.004(.002)*	0.002(0.001)
Land size	0.279(0.683)***	0.0247(.159)	-9.0934(4.048)
Access to credit	-0.0933(0.014)***	-0.116(0.096)***	-0.107(0.0643)***
Membership to farmer group	0.0276 (-0.1862)	-0.44(.0215)**	-0.703(0.201)**
Gender	0.232(0.311)	-0.49(0.25)***	-0.046(0.019)*
Intercept	1.412(0.448)**	1.68(1.473)	1.0087 (0.254)***

Note: *** = significant at 10 percent level; ** = significant at 5 percent level; * = significant at 1 percent level, (.) = standard errors.

Figure 1: Efficiency Distribution for Tomato Farmers