# TECHNICAL EFFICIENCY OF SMALL SCALE VEGETABLE GROWERS IN SRI LANKA: A COMPARISION OF PARAMETRIC AND NON-PARAMETRIC APPROACH

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***Abstract***

*Many researchers have depicted that most of the up-country vegetable growers have failed to capture technical efficiency due to poor managerial ability of economic resources. It is an undeniable fact that the majority of up-country vegetable farmers are characterized by poor socio-economic status. This paper investigates the resource use characteristics, profitability and technical efficiency of vegetable farming in a sample of vegetable farmers selected from 12 Grama Niladhary divisions in Nuwaraeliya District. The experiment sites were randomly selected based on a list of the Grama Niladhary divisions in Nuwaraeliya secretariat division and the empirical study was carried out based on a sample of 243 small scale vegetable farmers. This paper uses both parametric and non-parametric approaches to estimate technical efficiencies of vegetable farming at production and marketing stages under rain-fed condition in the up-country of Sri Lanka. The parametric approach was adopted under stochastic frontier production function with Cobb-Douglas form. The non-parametric approach in this paper was based on the data envelopment analysis technique in order to estimate technical efficiency of vegetable farming. Both parametric and non-parametric approaches have shown that the average technical efficiency estimates were not at potential level, and there is ample room for increased productivity through improving technical efficiency of vegetable farming. Under parametric approach, the average technical efficiency estimates at production stage and marketing stage were, 74.62% and 67.04%. Under non-parametric approach, the average technical efficiency was 70.86% and 62.84% at production and marketing stages, respectively. To examine consistency of the estimates from two approaches under different specifications, researcher applied independent sample t test, and the results show that the parametric and non-parametric approaches provide different estimates due to measurement and specification errors.*

***Keywords***: *Parametric and non-parametric approach, Profitability, Technical efficiency, Vegetable farming.*

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## INTRODUCTION

Vegetable sector has much potential in contributing towards the increase in the level of national income, export revenue, generate new employment opportunities, increase farm income and enhance nutrition and health of the people. Per capita consumption of vegetables in Sri Lanka remains far below the required average daily intake. The recommended daily intake of vegetables is at least 200g per day but an average Sri Lankan consume only about 94g per day, significantly below the recommended level (Ceylon Chamber of Commerce, 2017). According to the recommendations of the Medical Research Institute (MRI) per capita availability of selected vegetables need to increase to 80kg/year by year 2014. On average, the total cultivated extent of vegetables is around 93,000 ha and annual production is around 720,000 metric tons (Department of Agriculture, 2017). Out of total cultivated extent, around 32,000 ha are grown in upcountry category and the balance 40,000 ha, is functioning under low country category (Department of Agriculture, 2017). On average the country's vegetable productivity ranges from 5 to 15 tons per ha (Ceylon Chamber of Commerce, 2017).

There are two main groups of vegetables grown in Sri Lanka, based on the agro-ecological adoptability. The upcountry vegetable farming contributes crops such as beans, beetroot, cabbage, carrot, leeks, knolkhol and tomato which are grown on a commercial scale with high input use. Those introduced from other countries are called exotic vegetables and are usually cultivated in the cooler climate of the upcountry (Weerakkody, 2004). , where the land is scarce and the climate is favorable, throughout the year. Therefore, due to more reliable rainfall intensity and distribution, a wide range of vegetables are cultivated on a year round basis (Aberathna & Aberathna, 2002). Up-country farmers are usually practicing mono-cropping and multi-cropping in vegetable production. Average plot size is small (0.2-0.4ha) and cultivation is undertaken continuously with intensive labour, organic and chemical fertilizer and a high level of agro chemicals (Weerakkody, 2004). The second group is commonly known as low-country vegetables, which consists of ash plantain, ash pumpkin, okra, bitter gourd, brinjal, capsicum, cucumber, pumpkin, long beans etc. which are cultivated less intensively under the low input system. Seasonal rainfall in the dry zone allows for a seasonal production of fresh vegetables. On the other hand, Dry-zone vegetable production is characterized by shifting (*Chena*) cultivation in large areas with the adoption of poor technology. The application of fertilizers and use of improve cultivars are not widespread. Bulk of the shifting vegetables production comes during the *Maha* season (wet season) with little or no supplementary irrigation.

## PROBLEM STATEMENT AND CONCEPTUALIZATION

With economic growth and increasing population in Sri Lanka there will be an increased demand for vegetables in the local market and the supply has to be increased to match the increasing demand. To maintain price stability in the domestic vegetable market, the necessary conditions to be in tandem with the increasing consumer demand, the aggregate supply should be adjusted. Theoretically the demand for vegetable is derived demand and derivation commence from consumers. Consumers demand from retailers, retailers demand from wholesalers and finally wholesalers demand from producers (Fernando & Nilmini, 2010). Many professionals and reseachers have extensively discussed the slimmer profit margin of small scale vegetable growers as one of the main problems in the vegetable production industry in Sri Lanka (Esham & Usami, 2006; Mahaliyanaarchchi, 2004; Herath, 2007; Gunawardana, 1982). According to Kudagama (1998) more than 30-40% of all fruits and vegetables go to waste between harvesting and marketing, due to poor post-harvest handling. However, the absolute problems of this industry are, poor production technology, lack of markets and the under development of the processing and the export industry (Esham & Usami, 2006). Most of the farmers in hill country derive their primary income from vegetable farming and majority of them live below or within the poverty line (Fernando & Nilmini, 2010). Main reason for such poor income level is the technical inefficiency of vegetable farming at various stages. Mainly in production and marketing stage technical inefficiency is highly associated with the low level of income from vegetable farming. However, many publications have only highlighted the technical inefficiency at production stage, rather than at marketing stage.

According to Gunawardana (1982) the net price received by the producers were below 50% of the consumers retail price and the gross marketing margin for selected sixteen vegetables were above 50%. The highest portion of the gross margin is absorbed by the retailers and not by producers themselves (Gunawardana, 1982). More than 90% of the entire fruits and vegetables produce in the country are locally consumed as fresh products without any additional values (Esham & Usami, 2006). The majority of products are marketed through conventional channels and directed to low price markets. The transparency in the transaction between buyers and producers is relatively low among conventional vegetable supply chain. Higher degree of uncertainty still remains due to technical inefficiencies at production and marketing stages (Weerakkody, 2004). Most researchers and related professional studies have discussed the derivation of slimmer profit margin of up-country small scale vegetable farming, mainly due to technical inefficiency. However, relatively very little empirical effort has been made to measure the technical and allocative efficiencies of small scale vegetable farming in Sri Lanka. Consequently, it seems that there is a gap in the empirical knowledge available, especially in Sri Lanka with regards to efficiency measurements in up country vegetable farming. To the best of author's knowledge, there have been no studies, to estimate technical efficiency at marketing stage of small scale vegetable farming in Sri Lanka. Further, no studies were found comparing technical efficiency of vegetable farming under both parametric and non-parametric approaches. Therefore, this paper was the first attempt to do such an important analysis through parametric and non-parametric approach and made the comparison the outcomes in Sri Lankan context, under two approaches.

## ANALYTICAL FRAMEWORK

Technical efficiency is a measure of how well the individual transforms inputs into a set of outputs based on a given set of technology and economic factors (Kumbhakar & Lovell, 2000). Technical efficiency of an individual decision-making unit is defined in terms of the ratio of the observed output to the corresponding frontier output, condition on the level of inputs used by the firm (Russel, 1985; Battese, 1993). A firm is said to be technically efficient if it is producing the maximum output from a minimum quantity of inputs (Ziechang, 1984; Battese, 1993). There are two main competing paradigms for estimating the relative efficiency of individual decision making units (DMU); parametric and non-parametric. The parametric approach assumes a functional relationship between output and inputs and use statistical techniques to estimate the parameters of the function. The non-parametric approach, in contrast, contracts a linear piecewise function from empirical observations on inputs and output without assuming any a priori functional relationship between them. With non-parametric approach, data envelopment analysis (DEA) is used in estimating technical efficiency of each DMU.

### Parametric Approach

The original specification involved a production function specified for cross-sectional data which had an error term composed into two components: a stochastic random error component and a technical inefficiency component (Lovell, 1993). The model expressed in the following form: $Y = f(X_i\beta) + \varepsilon_i$ i = 1,.., N. Where $Y_i$ is the production (or the logarithm of the production) of the i-th firm; $X_i$ = Kx1 vector of input quantities of the i-th firm; $\beta$ = vector of unknown parameters; the essential idea behind the stochastic frontier model is that $\varepsilon_i$ term can be written as $\varepsilon_i = V_i + U_i$ . $V_i$ is the random variable which is assumed to be independently and identically distributed and independent of $U_i$ (Lovell, 1993).

Further, it is two sided ($-\alpha < V < \alpha$) normally distributed and random error that captures the stochastic effects outside the farmers control (Lovell, 1993). (E.g. weather, natural disaster and lucks). $U_1$ is non-negative random variables which are assumed to account for technical inefficiency in production and are often assumed to be independently and identically distributed and truncations (at zero) of the normal distribution or half-normal (Kumbhakar, Soumandra, & Thomas, 1991).

$U_i$ is a one sided $(U \geq 0)$ efficiency component that captures the technical efficiency of farmers. It measures the shortfall in output Y from its maximum value given by the stochastic frontier $Y = f\left(X_i \beta\right) + V_i$ .

### Non Parametric Approach – Data Envelopment Analysis

Data envelopment analysis (DEA) was developed by Charnes, Cooper, and Rhodes (1978) based on M.J Farrel's contribution to production efficiency. The data envelopment analysis technique uses linear programming method to construct a non-parametric frontier. The techniques also identifies efficient production units, which belong to the frontier, and inefficient once, which remain below it. DEA can handle multiple input and multiple output models; it does not require an assumption of a functional form relating inputs to outputs; decision making units (health centers) are directly compared against a peer or combination of peers; and inputs and outputs can have very different units of measurement.

### Empirical Model for Parametric Approach

In previous literature, different types of production functions have been adopted to discuss the frontier analysis. Among empirical literature, the most commonly applied production function is Cobb-Douglas (CD) production function and the transcendental Logarithm (TL) production functions (Baten et al., 2009; Battese & Corra, 1977; Hassan & Ahmad, 2005; Kachroo, Sharma, & Kachroo, 2010). The present study applied the Cobb-Douglas stochastic production frontier to estimate efficiency level at production and marketing stages under parametric approach. A DEA may be either input-oriented or output-oriented. Both output-oriented and input-oriented DEA models produce the same technical efficiency estimates for a firm under the assumption of constant returns to scale or variable returns to scale of production. If DMUs have more control over output variables than inputs variables, the DEA model should be output-oriented (Mahdi, Sghaier, & Bachta, 2008). However, in the case of vegetable farming, the producers usually have more control over their inputs than their outputs. Thus, in this study input-oriented models have been chosen for efficiency measurement under non-parametric approach.

### Model 1 Empirical model at production stage

The empirical model for Cobb-Douglas function forms at production stage is given by;

$$InY_i = \beta_0 + \sum_{j=1}^{6} \beta_{ij} InX_{ij} + V_i - U_i \, ,$$

*Where, ln denotes logarithms to base e and,* *Y = Output (Kg/ha), $X_1$= Extent cultivated (ha.), $X_2$= Family labour (man days), $X_3$= Hired labour (days/ha) $X_4$= Quantity of Fertilizer (NPK) (kg/ha)., $X_5$= Cost of machinery (Rs/ha), $X_6$ = cost of chemicals (Rs. /ha) and $\beta_0$ ,$\beta_1$……… $\beta_7$ are parameters to be estimated.*

**Model 2 Empirical models at marketing stage**

The empirical model for Cobb-Douglas function forms at marketing stage is given by;

$$InY_i = \beta_0 + \sum_{j=1}^{5} \beta_{ij} InX_{ij} + V_i - U_i$$

*Where, ln denotes logarithms to base e and,*
*Y = Average sold price (Rs/kg), X1 = Cost of grading (Rs/ha), $X_2$ = cost of cleaning (Rs/ha)*
*$X_2$ = cost of packaging (Rs/ha), X4 = cost of transportation (Rs/kg), $X_5$ = Applied Marketing Channel for sold the output (index)*

**Non- Parametric Approach – Data Envelopment Approach**

DEA is a novel approach to relative efficiency measurement where there are multiple incommensurate inputs and outputs. In that kind of scenario, efficiency is equal to weighted sum of outputs divided by weighted sum of inputs. Bousssofiane et al. (1991) express the DEA model as a fractional linear program of the following form:

**DEA Ratio Model**

$$TE_0 = Max \frac{\sum_r UrYrj_0}{\sum_j ViXij_0}$$

$$s.t \frac{\sum_r UrYrj}{\sum_j ViXij} \leq 1j \forall j$$

$$Ur, Vi \geq \varepsilon j \forall r, \forall i$$

*where: $TE_0$ is the technical efficiency score for decision making unit $j_0$; $U_r$ = the weight given to output r (r =1, ...,t and t is the number of outputs);Vi =the weight given to input I (i =1, ...,m and m is the number of inputs); n = the number of famers; t =the number of outputs; m=the number of inputs; ε = a small positive number; $Y_{rj}$ = amount of output r produced by farmer j; $X_{ij}$ =amount of input i used by farmer j; and $j_0$ = the decision unit under assessment.*

To ensure analytic tractability to linear programming methods this model can be converted into the following linear program under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). However, in the case of agriculture, increased amount of inputs do not proportionately increase the amount of output. At the initial stage, the study measured the technical efficiency under both CRS and VRS approaches and compared with parametric approach efficient measurement. It is important to note that the variation between parametric and non-parametric CRS methods is much higher than VRS method. Thus, this study focused only the VRS model for comparing technical efficiency of decision units under non-parametric approaches. However, the scale efficiency is equal to constant returns to scale technical score divided by variable returns to scale technical score which was not focused in this paper.

Input Oriented DEA – CRS Model

$$
\begin{aligned}
& Z_0 = Min\phi - \left(\sum_r S_r^+ + \sum_i S_i^-\right) \\
& s.t \\
& \sum_j \lambda_j X_{ij} + S_i^+ = \phi X_{ij0} \forall_i \\
& \sum_j \lambda_j Y_{rj} + S_r^- = Y_{ri0} \forall_r \\
& S_i^-, S_r + \geq 0_i, \forall_r \\
& \lambda_j \geq 0 \forall_j \\
& \varepsilon \succ 0
\end{aligned}
$$

Input Oriented DEA – VRS Model

$$
\begin{aligned}
& Z_0 = Min\phi - \left(\sum_r S_r^+ + \sum_i S_i^-\right) \\
& s.t \\
& \sum_j \lambda_j X_{ij} + S_i^+ = \phi X_{ij0} \forall_i \\
& \sum_j \lambda_j Y_{rj} + S_r^- = Y_{ri0} \forall_r \\
& \sum_i \lambda_i = 1 \\
& S_i^-, S_r + \geq \forall_i, \forall_r \\
& \lambda_i \geq 0, \forall_j
\end{aligned}
$$

where λj are dual variables, i.e. the shadow prices related to the constraints limiting the efficiency of each DMU to be no greater than 1. Where a constraint is binding, a shadow price will be normally positive and when the constraint is nonbinding the shadow price will be zero. In the solution to the primal model therefore a binding constraint implies that the corresponding DMU has an efficiency of 1 and there will be a positive shadow price or dual variable. Hence positive shadow prices in the primal, or positive values for the λj in the dual correspond to and identify the peer group for any inefficient unit. Sr and Si are slack variables; if DMU $j_0$ is efficient, the slacks will equal to 0 and the efficiency measure $Z_0$ equal to 1. Otherwise, if $j_0$ is inefficient $Z_0$ will be less than 1 and some slacks may be positive.

**Final Empirical Models for Non- Parametric Approach**

The model is presented here for the situation with number of N decision making units, each producing a single output, vegetable, by using different inputs. Here, $Y_i$ is the vegetable output and $X_i$ is the (m x 1) vector of inputs used by the $i^{th}$ DMU. Y is the (1 x n) vectors of output and X is the (m x n) matrix of inputs of all N DMU in the sample and since present study observed 243 small scale vegetable growers, (N=243).

The DEA model to calculate the technical efficiency is;

$$Min_{\phi\lambda}\phi$$

Subject to

$$-y_i + Y\lambda \geq 0$$
$$\phi_i x_i - X\lambda \geq 0$$
$$\sum_{i}^{n} \lambda_j = 1$$
$$\lambda \geq 0$$

Where, $\phi_i$ is a TE measures of $i^{th}$ DMU and λ is an n x 1 vector of weights attached to each of the efficient DMUs. A separate linear programming (LP) problem is solved to obtain TE score for each of the n DMUs in the sample. If $\phi$=1, the DMU is on the frontier and is technically efficient under CRS. If $\phi$<1, then the DMUs lies below the frontier and is technically inefficient. In the case of agriculture, any output improvement does not proportionally increase the amount of output. Hence, the model is dealing with VRS which is more realistic implication in vegetable farming in the up-country. Similar variables which have applied under parametric approach were considered for measuring technical efficiency of selected vegetable producers at production and marketing stage.

**Study Locations**

The up-country of Sri Lanka consists primarily of mountainous terrain. The climate is cool and many areas about 1500 meters above the see-level often have chilly nights. The western slopes are very wet, some places receiving almost 7000 mm rain per year (Weerakkody, 2004). The eastern slopes are part of the mid dry-zone receiving rain only from North-Eastern Monsoon. There are three administrative districts in up-country, namely, *Nuwaraeliya, Mathale and Kandy*. The present study covered only the *Nuwaraeliya* district. There are five D.S divisions in *Nuwaraeliya* District as *Kothmale, Haguranketha, Walapane, Nuwaraeliya and Ambagamuwa*. The study chose Nuwaraeliya Divisional Secretariat (D.S) division. Further, there are 72 *Grama Niladhari* (G.N) divisions in Nuwaraeliya D.S division and study randomly selected 12 G.N divisions.

**Sampling Framework and Data Gathering Tools**

The target population of the field survey was 242 vegetable farmers in 12 G.N divisions in the *Nuwaraeliya* D.S area in the *Nuwaraeliya* District. Their income, mainly depends on vegetable farming and related activities. A cross-sectional survey method was used to collect the data with a structured questionnaire. Multi stage cluster sampling techniques were used to select the decision making units under two stages. At the first stage farmers were clustered based on cropping patterns as mono cropping (Those who have cultivated one type of vegetable) and multi cropping (those who have cultivated number of vegetable in the same plot or in different plots) (Mahaliyanaarchchi, 2004). Since, more than 80% of population farmers recorded multi cropping farming method in the study area; the study only selected multi cropping farmers for field survey. Secondly, to maintain the consistency of the study, the field survey was carried out among the farmers who cultivated vegetables such as, carrot, leaks, beetroot and cabbage. This is due to the fact that the cost of production, profit margin and selling prices of such vegetables do not reflect a significant variation among small scale vegetable growers. Population and sample size are presented in Table 1.

**Table 1: Population and Sample Size of each G.S. Division**

| Name of G.N Division | Total no of Multi Cropping vegetable Growers | Sample Size | Name of G.N Division | Total no of Multi Cropping vegetable Growers | Sample Size |
|---|---|---|---|---|---|
| Bogahawattha | 54 | 21 | Hewaeliya North | 42 | 18 |
| Kandapola | 44 | 18 | Seethaeliya | 68 | 26 |
| Bambarakele | 52 | 21 | Kalukele | 62 | 24 |
| Kuduoya | 38 | 16 | Parakumpura | 50 | 20 |
| Thalawakele | 34 | 15 | Kirimatiyaya | 44 | 18 |
| Lindula | 62 | 24 | Shanthipura | 55 | 22 |
| | | | | 725 | 243 |

## RESULTS AND DISCUSSION

### Cost of Production, Returns and Profitability

Cost of production, profitability and returns to resource unit of selected crops on average basis are presented in Table 2. The cost structure does not vary significantly among selected crops. The total cost of production mainly consists of two components as labour and materials. Labour cost is the major component in cost structure and it contributed to more than 40% of total cost for all selected crops, reflecting a labour intensive production approach. Both gross returns and net returns were highest for cabbage and lowest for beetroot. The net income variation between these two crops was Rs. 28,687 per ha. The highest returns to labour and capital were recorded under cabbage and lower under leeks production. Among selected crops, the highest break-even yield was reported under cabbage production and lowest under carrot production.

**Table 2: Average cost, Returns and Profitability**

| Items (Rs/Ac) | Beetroot | Cabbage | Carrot | Leeks |
|---|---|---|---|---|
| Land Preparation cost | 6,800 | 7,450 | 7,890 | 8,800 |
| Labour cost | 78,250 | 77,860 | 80,560 | 82,000 |
| Materials cost | 67,240 | 74,560 | 77,565 | 79,780 |
| Processing cost | 12,450 | 18,760 | 15,500 | 18,890 |
| Total Cost | 164,740 | 178,630 | 181,515 | 189,470 |
| Average Yield (Kg/Ac) | 5,645 | 6,875 | 5,520 | 5,425 |
| Selling Price (Rs/Kg.) | 43.00 | 41.50 | 49.80 | 50.15 |
| Gross Income | 242,735 | 285,312 | 274,896 | 272,063 |
| Net Income | 77,995 | 106,682 | 93,381 | 82,593 |
| Cost Per Kg | 29.2 | 25.9 | 32.8 | 34.9 |
| Profit per Kg | 13.8 | 15.5 | 16.9 | 15.2 |
| Return to Labour (Rs/day) | 847 | 1,159.6 | 983 | 860 |
| Return to Capital(Rs/unit) | 1.15 | 1.43 | 1.16 | 1.03 |
| Break-even Yield (kg/ac) | 3,831 | 4,304 | 3,645 | 3,778 |

Source: Author computation based on Field Survey 2017

**Estimated stochastic frontier Cob Douglas Functions Under parametric Approach**

Estimated parameters of stochastic production function with Cobb-Douglas form at production stage and marketing stage are presented in Table 3. The ratio of the standard error of u to that of v which is the λ for production stage is 2.476 and marketing stage is 1.528 exceeded one in value and statistically different from zero at the one percent significant level. This is an important parameter of log likelihood in the half normal model and correctness of the specific distributional assumption. If λ = means, there are no technical inefficiency effect and all deviation from the frontier are due to statistical noise. However, in this study since both λ is significantly different from zero for both functions, it suggested the existence of an inefficiency effect for up-country vegetable farming at production and marketing stages.

The strength of the inefficiency and random effect can be separately observed using the value of γ. The γ is the ratio of the variance of farm specific technical efficiency (u) to the total variance of output. Both models showed that frontier output was dominated by technical inefficiency. As expected, the signs of the estimated parameters of both stochastic production frontiers are positive and highly significant unless machinery application. The estimated parameter for machinery usage showed the conventional positive input output relationship, while it was not statistically significant. This is, because in hill country, machinery application is limited and does not much impact on productivity. The estimation of the Cobb-Douglas production function at production stage shows that the output elasticity of family labour (0.673) had the highest impact on productivity among selected variables. The second important variable was extent cultivated and thirdly, chemical application. At the marketing stage, the highest output elasticity was shown in the type of marketing channels. However, grading, cleaning, packing, and transportation also have significant impact on average selling price.

**Table 3: Estimated Cobb Douglas production Function at Production and Marketing Stages**

| Variables | Para. | MLE estimates Production Stage | | MLE Estimates Marketing Stage | |
|---|---|---|---|---|---|
| | | Coefficients | T-Ratio | Coefficients | T-Ratio |
| Constant[a] | $\beta_0$ | -3.909* | -6.357 | | |
| Constant[b] | | | | -1.749* | -3.943 |
| Extent Cultivated (X1)[a] | $\beta_1$ | 0.527* | 3.904 | | |
| Cost of Grading (X1)[b] | | | | 0.344* | 4.360 |
| Family Labour (X2)[a] | $\beta_2$ | 0.673* | 2.938 | | |
| Cost of Cleaning(X3)[b] | | | | 0.158* | 3.592 |
| Hired Labour (X3)[a] | $\beta_3$ | 0.487** | 2.628 | | |
| Cost of Packaging (X3)[b] | | | | 0.130* | 3.290 |
| Fertilizer usage (X4)[a] | $\beta_4$ | 0.368* | 4.272 | | |
| Transportation Cost(X4)[b] | | | | 0.485* | 4.449 |
| Machinery exp. (X5)[a] | $\beta_5$ | 0.285 | 1.271 | | |
| Marketing channal (X5)[b] | | | | 0.654* | 4.276 |
| Cost of chemicals (X6)[a] | $\beta_6$ | 0.459* | 4.267 | | |
| Sigma Square | $\sigma^2$ | 0.117 | | 0.543* | 11.668 |
| Log-Likelihood Function | | -141.860 | | -100.896 | |
| Sigma | $\sigma$ | 0.342 | | 0.737 | |
| Sigma-Squared (u) | $\sigma_u^2$ | 0.294 | | 0.516 | |
| Sigma-Squared (v) | $\sigma_v^2$ | 0.048 | | 0.221 | |
| Lamda $(\sigma_u / \sigma_v)$ | $\lambda$ | 2.476 | | 1.528 | |
| Gamma | $\gamma$ | 0.859 | 98.76* | 0.70* | 80.45 |
| LR test - one-sided error | | 68.796 | | 81.929 | |
| Mean Efficiency | | 74.62% | | 67.04% | |

Note: * and ** are significant at 1 percent and 5 percent consecutively. [a] depicted exogenous variables for production stage and [b] denote exogenous variables for marketing stage.

**Technical Efficiency under Parametric Approach**

Having obtained the estimates of production structure, the next step was to analyze the technical efficiency score of each farmer at production and marketing stages under both parametric and non-parametric approaches. The frequency distribution of technical efficiency scores under parametric approach is presented in Table 4.The mean technical efficiency level at production stage was 74.62% and 67.04% at production and marketing stage respectively.

This indicated that the up-country vegetable productivity of the “average farmer” could be further increased by 25.38% without any additional resources at production stage and their net income could thereby be further increased by 32.96% at marketing stage by adopting proper resource management practices. According to efficiency scores, marketing stage inefficiency has driven more losses to stakeholders than the production stage. At production stage, 37.9% stakeholders were reported less than 60% technical efficiency level. However, at marketing stage more than 31.6% stakeholders showed less than 60% technical efficiency

**Table 4: Distribution of Technical Efficiency under Parametric Approach**

| Efficiency Level | Production Stage | | Marketing Stage | |
|---|---|---|---|---|
| | Number of Farmers | Percentage | Number of Farmers | Percentage |
| 20-30 | 1 | 0.4 | 3 | 1.2 |
| 31-40 | 3 | 1.2 | 10 | 4.1 |
| 41-50 | 8 | 3.3 | 20 | 8.2 |
| 51-60 | 31 | 12.8 | 44 | 18.1 |
| 61-70 | 49 | 20.2 | 97 | 40.0 |
| 71-80 | 89 | 36.6 | 28 | 11.5 |
| 81-90 | 32 | 13.2 | 22 | 9.1 |
| 91-100 | 30 | 12.3 | 19 | 7.8 |
| Total Farmers | 243 | | 243 | |
| Mean Efficiency | 74.62% | | 67.04% | |

Source: Author’s computation based on frontier analysis

**Technical Efficiency under Non-Parametric Approach**

The frequency distribution of technical efficiency scores under parametric approach is presented in Table 5 and it shows that there was a wide range of technical efficiency differences. The mean technical efficiency score at both stages are less than the parametric approach. At production stage mean technical efficiency was 70.86% and marketing stage it was 62.84%. The minimum technical efficiency level was only 0.4% at production stage and 1.2% at marketing stage, while, maximum level was 12.3% at production stage and 7.8% at marketing stage. It is important to note that, under non-parametric approach both upper tail and the lower tail of the efficiency scores have been increased and middle part of the efficiency score has declined at both production and marketing stages. According to non-parametric approach, 37.5% and 32.2% stakeholders recorded less than 60% efficiency level at production and marketing stage respectively. Thus, compare to parametric approach the efficiency level of respective range (below 60%) did not show much variation.

**Table 5: Distribution of Technical Efficiency under Non-Parametric Approach**

| Efficiency Level | Production Stage | | Marketing Stage | |
|---|---|---|---|---|
| | Number of Farmers | Percentage | Number of Farmers | Percentage |
| 20-30 | 2 | 0.8 | 6 | 2.5 |
| 31-40 | 5 | 2.1 | 17 | 7.0 |
| 41-50 | 10 | 4.1 | 23 | 9.5 |
| 51-60 | 33 | 13.6 | 32 | 13.2 |
| 61-70 | 41 | 16.9 | 73 | 30.0 |
| 71-80 | 73 | 30.0 | 32 | 13.1 |
| 81-90 | 37 | 15.2 | 28 | 11.5 |
| 91-100 | 42 | 17.3 | 32 | 13.2 |
| Total Farmers | 243 | | 243 | |
| Mean Efficiency | 70.86% | | 62.84% | |

Source: Author's computation based data envelopment analysis.

### A comparison of parametric and Non-Parametric Estimates

Present study applied two approaches to measure the technical efficiency of up-country vegetable farmers, in which the parametric approach was based on SFPF technique while the non-parametric approach was based on DEA technique under the assumption of Variable Returns to Scale (VRT). The study hypothesized that efficiency estimates derived from one approach might not be more (or less) than that of other techniques. However, the study found that, non-parametric mean efficiency score was around 4% and 5% less than the parametric approach at production and at marketing stage respectively. Besides, the study found that both upper and lower sections of the efficiency scores to have increased and middle part quite reduced under non parametric approach. Why did such a deviation occur under the same assumption on VRS under different approaches and why is that the difference is significant? For that purpose, the study applied independent sample T test to measure the significance of efficiency scores variation which had been obtained by each stakeholder under both approaches, at production and marketing stages. The results are presented in Table 6.

**Table 6: Comparison of Efficiency Scores between Different Approaches**

| Stages | TE on PA | TE on NPA | T-Ratio | Probability | Effect Size |
|---|---|---|---|---|---|
| Production | 74.62% | 70.86% | 3.465 | 0.001 | 0.167 |
| Marketing | 67.04% | 62.84% | 3.233 | 0.001 | 0.156 |

Note: An effect size (r) is an objective and standardized measure of the magnitude of the observed effect. As per Cohen (1988, 1992) r = 0.1; small effect, r=0.3; medium effect and r=0.5 large effect.

The results show that, on average, the estimated Technical efficiency scores of each stakeholder at production as well as at marketing stages were significantly different between parametric and non-parametric approaches. This is not so much of a surprising outcome, since most literature have showed same comment during the past decades (Minh & Long, 2009; Drake &d Jones, 1996; Ferrir & Lovell, 1990; Kalaitzadonkes & Dunn, 1995).

## CONCLUSION AND RECOMMENDATIONS

The present study applied and compared both parametric and non-parametric approaches in estimating technical efficiency of up-country vegetable farmers at production and at marketing stages. The parametric approaches carried out under stochastic frontier analysis with Cobb-Douglas production function assuming error term is half normal distribution. Non-parametric approach was based on DEA model. Both approaches measured the output oriented technical efficiency with VRS assumption.

Under parametric approach, average technical efficiency was 74.62% at production stage and 67.04% at marketing stage, while, under non-parametric approach, it was 70.86 at production stage and 62.84% at marketing stage. In fact, those findings indicate that up-country vegetable growers are functioning far below the potential efficiency level at production as well as at marketing stage. On average, at production stage stakeholders could increase their productivity around 30% and at marketing stage it would be possible to increase it to around 35%, subject to existing resource levels. In other words, by operating at full technical efficiency level at production and marketing stages, the sampled stakeholders would be able to reduce their existing cost of production by around 35%. This is important in two ways, one is resource optimization and other is profit maximization. If vegetable farmers can reduce their cost of production by 35% without reducing their productivity, it will positively directly impact on profit margin of vegetable farming.

Thus, policy maker's attention on technical efficiency improvement at production and marketing stages are a timely need, which will lead to a better living condition for the small scale vegetable farmers, by gaining a better profit margin. The policy makers and rated professionals have given much attention in improving market margin at marketing stage of vegetable growers rather than profit margin at production stage. However, from the economic point of view, both, the consumer as well as the producer could be better off, if producers can improve their productivity through technical efficiency that will ultimately leads to optimizing available resources in the country.

The comparison of the estimated efficiency scores from these two approaches show that the results are significantly different, in which parametric approach produced higher estimates than non-parametric approach. The different results may be due to various reasons, such as estimation procedure, measurement and specification errors, number of observations, number of explanatory variables and type of data in which time serious or panel.

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