Training technology nexus and technical efficiency of apple farmers: an application of stochastic frontier approach

Recebimento dos originais: 06/12/2019
Aceitação para publicação: 08/04/2020

Xiu-yun Yang
Faculty
School of Economics and Finance,
Xi'an Jiaotong University Shaanxi P.R.China.
E-mail: yangxiuyun@mail.xjtu.edu.cn

Nadeem Akhtar Khan (Corresponding Author)
Doctoral Researcher Applied Economics
School of Economics and Finance
Xi'an Jiaotong University Shaanxi P.R.China.
Department of Agriculture Gilgit-Baltistan Pakistan.
E-mail: khan.nadeemakhtar@hotmail.com

Samina Mumtaz
Faculty
Department of Biological Sciences
Karakorum International University Gilgit Pakistan
E-mail: samina@kiu.edu.pk

Waheed Ali
Doctoral Researcher Applied Economics
School of Economics and Finance
Xi'an Jiaotong University Shaanxi P.R.China.
E-mail: aliwaheed@stu.xjtu.edu.cn

Hadi Hussain
Doctoral Researcher Applied Economics
School of Economics and Finance
Xi'an Jiaotong University Shaanxi P.R.China.
E-mail: hussainhadi@stu.xjtu.edu.cn

Abstract

This study investigated the training technology nexus and technical efficiency of apple growers. In order to gauge the impact of training and technology on the technical efficiency of apple growers, we adopted Maximum Likelihood Estimates based on Stochastic Frontier Analysis. The empirical findings suggest that the training presented a negative effect on technical inefficiency of apple farmers and while the technology revealed positive relationship with technical inefficiency. Training tends to reduce the technical inefficiency while technology tends to augment inefficiency among the apple growers. This conduct of technology can be due to incompatible existing knowledge, environment, and resilience of farmers. Empirics of this study observed the range of technical efficiency scores between 0.43

minimum and 0.99 maximum with mean technical efficiency of 0.92 among apple farmers. The mean value of technical efficiency suggests that each farmer's production efficiency level was at 92% with existing inputs and production technology. The calculated RTS value 0.78 <1 for the whole sample which implied that apple farmers were operating under constant return to scale regime.

Keywords: Training. Technology. Technical Efficiency.

1. Introduction

Efficiency analysis and estimation is a pragmatic approach in applied economic literature typically adopted to gauge the performance of decision-making units (DMU) extensively applied to every sector of the economy including the agriculture sector. Efficient utilization of factor inputs plays a significant role in production systems and inappropriate combination or misuse of inputs causes inefficiency. Measuring efficiency in the agriculture sector is crucial for the development sector and it provides useful information to devise policies (Dessale, 2019).

1.1. Training-technology nexus

The implementation of technological advancement in farm operations is imperative to keep farm production systems productive and efficient. The theory of technological treadmill was the brainchild of (Cochrane, 1958) postulates that those farmers realize higher gains who adopted new technology early and gains emanating from new technology steadily removed as more and more farmers adopt it. Despite the invention of modern technology and the discovery of advance knowledge, sizeable rural communities around the world still lack access to these amenities. The potentials of technology in production systems are extensively accepted but accurate alignment and magnitude of possible conversions are mysterious (FAO, 2004).

Analysis of the related empirics from least developed economies will help us to establish a linkage among core interests of this study i.e. training-technology nexus and technical efficiency. (Karimov, 2012) stated that, the facility of agricultural training and establishment of agricultural advisory services helps farmers to obtain new technology and built capacities in farm production decision making ultimately improved resource utilization and efficiency. In line with the earlier argument (Njine, 2014) argued and confirmed the role of training infrastructure and noted that the establishment of extension training centers plays a vital part in the dissemination of knowledge and technology transfer among farmers.

Advanced training and education in farm-specific innovative technologies help farmers to acclimatize with an innovative technological environment. Ultimately, the collusion of the efficient labor force and innovative technology-led improvement in efficiency at the farm level and better productivity eventually (Sauer et al, 2014). Later on (Danso-Abbeam. et al, 2018) indicated similar findings that agricultural extension programs have been instrumental in disseminating knowledge related to farm technologies, help farmer's informal education and assist in improving their technical skills and farm management.

(Abdullahi et al, 2015) found an increase in agricultural productivity due to the adoption of technology, and also recommends the provision of training for farmers related to utilization and implementation of newly adopted technology and these findings were endorsed by (Abdul et al, 2019) noted that adopters of new production technology were 10% more technically efficient than non-adopters. Moreover (Parke, 2013;) examined the effects of the introduction of technology in agriculture and this introduction yields enormous growth in food productivity. Similarly, (Ahmad et al., 2007; Khan, 2018; Alemu et al, 2018) revealed that well-trained and informed farmers along with advanced production technology can make a transformation in efficiency and productivity. Another study also revealed that self-learning through practice did not apparently increase farm efficiency. This study further established a direct relationship among the training, education and farm efficiency (Tariq et al, 2018; Nguyen et al, 2019).

In this section, we tried to established the causal relationship among training, technology and technical efficiency of farmers through the available existing literature in this pathway. On the basis of this textual analysis of literature, we have developed a model to illustrate the relationship between training technology nexus and technical efficiency.

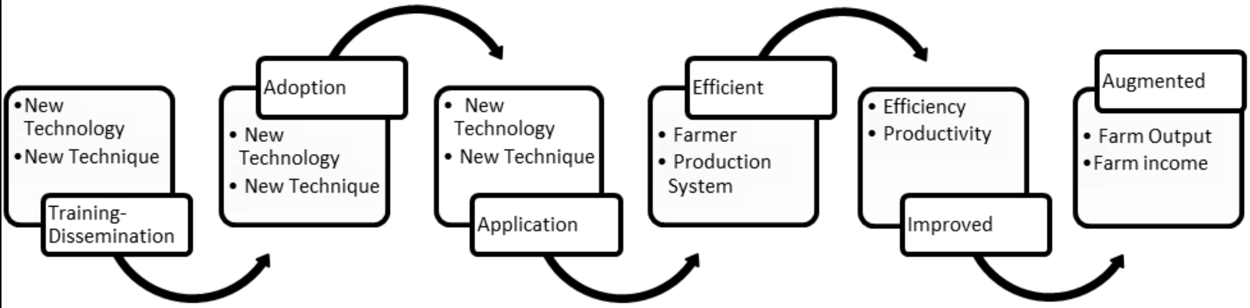

Figure 1: Theoretical Model
Source: Author's own construction

1.2. Factors affecting technical efficiency

Farm production is a complex process and it depends on various endogenous and exogenous factors that affect farm performance. Whereas previously we shed light on the contributions of knowledge and technology in farmer's efficiency and productivity. In this part, we will analyze the factors affecting farmer's technical efficiency. It has been proven from the empirical inquiries across the farming communities around the world that, farm efficiency does not influence by any single factor rather differentials in technical efficiency are attributed to various tangible and intangible elements.

The level of technical efficiency also affected by farm management practices and overall farm's social and environmental (Sidhoum et al, 2019). On the other hand, the farmer's resilience towards policy change and adaptability also contributes to efficiency, young farmers interested to adopt new technology and knowledge as compared to old farmers (Martinez et al, 2018; Skevas et al, 2017). Similarly, (Wang et al, 2013) revealed that the technical inefficiency among the apple growers in Shaanxi province affected due to inefficient farm operations and unfavorable climatic conditions. Three Chinese provinces Shaanxi, Shandong, and Gansu experienced higher technical efficiency for the apple farmers who owns the membership of cooperative societies compared to non-member farmers because these cooperative societies help the farmers to advance new technology and new knowledge (Ma et al, 2018).

Some empirical investigations tried to reveal the factors affecting technical efficiency of various crop producers across the world. Numerous other variables e.g. farmer's level of education, age contact with agricultural advisory services produce a substantial impact on technical efficiency (Hossain et al, 2015; Trujillo and Iglesias, 2013). And other researchers like (Karani-Gichimu et al, 2015) while evaluating technical found that level of schooling, frequency of advisory facilities uses and market access significantly affect the technical efficiency of passion fruit farmers. Similarly, (Ahmadzai, 2017) noted the significant positive impact of crop diversification on farmer's technical efficiency and other factors such as farm size, access to agricultural advisory services and tractor owned also a significant effect on technical efficiency. In line with earlier elaborated conclusions (Balogun et al, 2018) affirmed and identified the significant effects of agricultural extension services on technical efficiency and further elaborated that the productivity of pineapple significantly affected by quantities of fertilizer, herbicide and hired labor applied.

Access to credit is an important factor that facilitates new investment to replace the existing farm technology (Chiona et al, 2014) pointed that along with other factors access to credit was one of the most influential contributors to technical efficiency. The findings of (Murtaza and Thapa, 2017) also pointed positive significant impact of credit facility and other variables on the technical efficiency of apple farmers. While (Ullah et al, 2018) exposed some important elements e.g. family size, price volatility, natural calamities and climatic shock off-farm income, posed negative effect on peach's farmers technical efficiency Later on (Chandio et al, 2019) confirmed these findings by investigating the relationship between access to credit and technical efficiency noted significant effects of access to credit on farmer's productivity and technical efficiency.

The fundamental objective of this study is to evaluate the training-technology nexus and factors affecting technical efficiency of apple farmers. This review of literature tried to build logical linkages between training-technology and technical efficiency. However, it has been revealed from the thorough analysis of literature that, the realm of training-technology nexus and technical efficiency still needs to be investigated across the agricultural sector.

1.3. Output oriented efficiency

A substantial amount of empirical literature on the production efficiency of firms across the sectors is available in economic literature. Efficiency can be classified into two parts technical efficiency deals with output-oriented and input-oriented. In the output-oriented estimation of technical underproduction, we can evaluate the firm's ability to maximize the production keeping input constant as output allows. In other words, it assesses the producer's ability to the efficient utilization of available economic resources with existing technology to maximize output. While the input led measure of technical efficiency examines the producer's capability to restrain the wastage of input keeping output constant.

This study deals with output-oriented technical efficiency, for our understanding, we adopted a figure from (Coelli et al, 2005). In the illustration, we suppose a situation in which production comprises two products (q1 q2) and a single input factor (X1) assuming constant with a given technology attributed CRS property Z' Z which represents production possibility curve. Point A represents an inefficient farmer located below the curve of feasible production at point B represents the upper limited of output possibilities. Distance between A and B represents the technical inefficiency and farmer confronted with underproduction which could be augmented without raising the additional quantity of inputs. Thus Farrell's (1957) output-oriented technical efficiency can be estimated as TE= OA/OB and allocative efficiency can be calculated as AE= OB/OC.

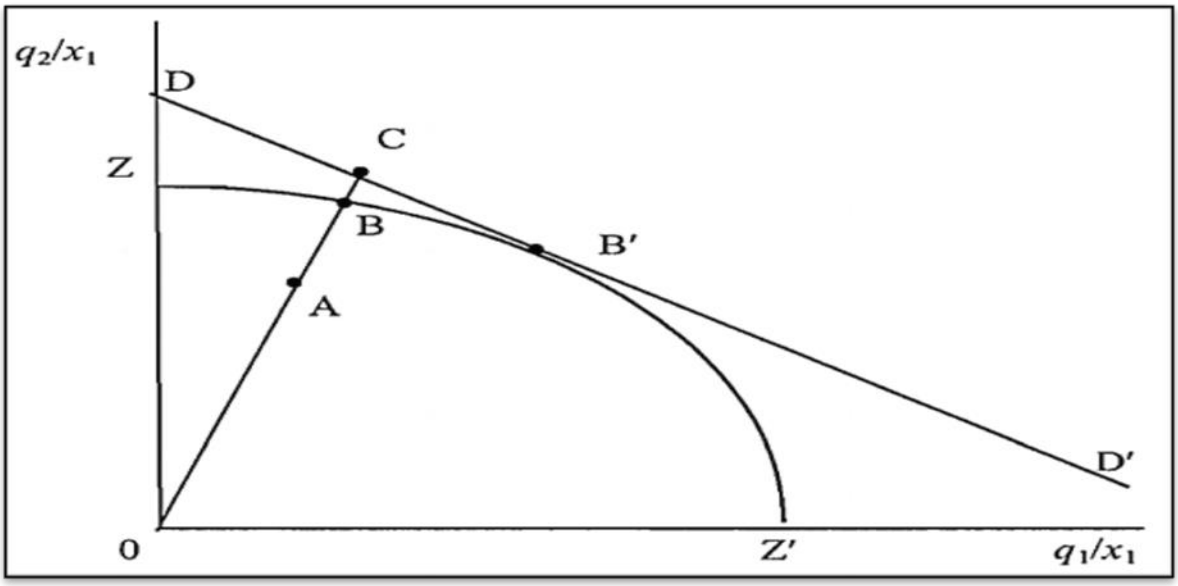

Figure 2: Farrell's output-oriented technical efficiency

Source: Espoused form Coelli et al., (2005)

2. Methodology

The progress of scientific studies on the efficiency of decision-making units has gained momentum after the emergence of (Farrell's 1957) influential work. The stochastic frontier approach is the most frequently used approach to conduct the appraisal of the technical efficiency of farms. The SFA approach measures the parametric form of the production function; this approach presents the stochastic disturbance term in the data consisting of two parts one term explains the efficiency and the second term defines the random effects beyond the control of the producer.

The production frontier is stochastic in its nature as it fluctuates arbitrarily across the farms due to the existence of the random stochastic term (T. J. Coelli, 1995). This method presented the first time in empirical literature by (Aigner et al, 1977; Meeusen and Van, 1977). Data envelopment analysis (DEA) is an alternative approach to estimate technical efficiency does not prerequisite the production function to be parametric. This assumption implies that the unobservable factors beyond the control of the producer do not influence productivity. In the case of the agriculture sector, this assumption becomes an impediment while observing natural phenomena weather and climatic conditions that significantly upset the model. To coup with this problem, we proposed a stochastic frontier model, as it allows us to analyze the factors in control and beyond control as well (Aigner et al, 1977; Kumbhakar, 2015).

2.1. Validity and hypothesis tests

Irrespective of the selection of distributions, as the likelihood function of the stochastic frontier model, is extremely nonlinear its estimation can be complex. In order to coup with this obstacle, it is ideal to conduct appropriate tests to ensure the validity of stochastic frontier specifications before adopting the highly complex maximum likelihood (Kumbhakar and Wang, 2015; Kumbhakar and Wang, 2010). Apart from the skewness test on OLS residuals, (Coelli et al, 1999) suggests another test called M3T statistics a variant of the above test, however; we adopted the test of skewness on OLS residual. This test allows us to evaluate the compatibility of the stochastic frontier specification.

Apple farmer is classified by heterogeneity in multifaceted attributes of farm household i.e. resources owned, farming practices and other socio-economic dynamics that could probably cause the differentials in their individual efficiency. In order to test the hypothesis, this inquiry adopted a test of likelihood ratio LR= -2[L (H•) –L (H1)] whereas L (H•) and L (H1) represents the statistic of log-likelihood function beneath null hypothesis and alternative hypothesis respectively (Greene, 1980).

If the estimated chi-square is greater than critical chi-square with a degree of freedom (A condition with the number of parameters equal to zero under the null hypothesis) at 1 %, 5% and 10% level of significance, the hypothesis will be rejected. i.e. LR> $X\, C^2$ (Kodde and Palm, 1986).

- To adopt suitable functional form which could represent the data appropriately. Therefore, the suitability of Cobb- Douglas production function and Translog production function shall be established.
- A hypothesis was tested to ascertain the appropriateness of adopting the Stochastic Frontier Model over OLS. The inefficiencies among the farmer are stochastic and inefficiency attributes do not exist in the model at each step and combined effects of these variables on technical efficiency are significant statistically. In case if the null hypothesis is accepted, the stochastic frontier could not be shifted to OLS condition. In this situation, if there are output differentials among growers are provided with equivalent input factors. This differential is purely due to inefficiency among the farmers.
- This null hypothesis classifies the observed effects of the factors (Farm, socio-economic and geographic-climatic factors) affecting technical inefficiencies equal to zero.
- In order to select feasible distribution which best fits model, if this null hypothesis is rejected we will opt truncated normal distribution over half-normal distribution.
- The postulated null hypothesis specifies that the production function exhibits an increasing return to scale. To analyze the production function whether a constant return or decreasing and increasing exists in the model, the Wald test shall be commissioned.

Table 1: Hypothesis Test

Null Hypothesis	T-Statistics	P-Value	Decision
Cobb-Douglas vs. Translog			
H0: β1=β2= β3=...βn=0	LR chi2(1) = 273.65	***	Rejected
Frontier Model Specification Test			
H0: γ=δ0=δ1=...δn=0	M3T= -1.36(LR=78)	***	Rejected
H0: δ0=δ1= δ2=... δn=0	LR chi2(8) = 67.23	***	Rejected
H0: $\_ = ii\_\_+(0, \sigma\_2)$	LR chi2(1) = 47.08	***	Rejected
Return to Scale Test			
H0: $\sum \beta\_ = 1$	Wald (x^2)= 948.06	***	Rejected

Source: Author's own estimations

The findings derived from the stochastic frontier model could be substantially influenced by functional farm adopted. Cobb-Douglas and Translog production are being extensively employed in the analysis of production functions. Under this study, we selected these two specifications of the stochastic frontier function for comparison purposes.

In order to test the first hypothesis a generalized log-likelihood ratio test was conducted to adopt the suitable functional method. The estimated LR statistic was 27.65 at 1 degree of freedom that is larger than the x^2 critical statistic 5.41 at a 1% level of significance, consequently Cobb-Douglas functional form preferred over Translog functional form.

The second hypothesis was tested to diagnose the existence and absence of technical inefficiency effects based on the log-likelihood value of OLS and estimation of stochastic frontier based on maximum likelihood. In this regard, the estimated LR statistic was 78 at 1 degree of freedom which is greater than the x^2 critical value 5.41 at a 1% level of significance and the null hypothesis that technical inefficiency effects are absent in the data are rejected. The conventional OLS based production function is not a suitable illustration of sample data in our case; however, this outcome was also supported by the results of the M3T test untaken before.

In order to test the third hypothesis whether explanatory variables involved in the inefficiency segment of the model are equal to zero or not. To acquire this objective, we engaged the LR test to estimate the value by adopting the value of log likelihood-based stochastic frontier production without explanatory variables of inefficiency effect approach and complete model along with explanatory variables of inefficiency effect estimated. Estimated LR test measurement is 67.23 with 8 degree of freedom that is greater than the x^2 critical statistic of 19.38 at a 1 % significance level. The result derived from the calculation of the LR test statistic, the null hypothesis was failed to get accepted at a 1% significance level. Consequently, independent variables in the inefficiency effect segment of the model are jointly different from zero.

Under the hypothesis fourth, to confirm the distributional statement of the inefficiency termui, two models were built based on half-normal distribution and truncated normal distribution for the single-ended error as stated. The LR test was engaged to compute the test statistic by the log-likelihood based on the value of the stochastic frontier model implementing half normal and truncated normal on the inefficiency model. Computed LR value is 47.08 at 1 degree of freedom that stands larger than x^2 critical value of 5.4 at a 1% level of significance. On the bases of this finding null hypothesis is rejected and truncated normal distribution is preferred over half normal.

The fifth hypothesis was tested to; weather production model demonstrates an increasing return to scale. The calculated value of the Wald test was x^2 948.06 with a p-value of 0.000 therefore null hypothesis of increasing return to scale is failed to accept as the stated.

2.2. Experimental stochastic frontier model

The stochastic frontier model can be express in this method.

$$Y_i = f(Xi, \beta) e^{vi-ui} \quad (2)$$

Whereas Y_i designates the output of the i-th farmer, and Xi denotes a (1×k) vector of the productive elements of the i-th farmer, β is a (k×1) vector unfamiliar production elasticity parameter to be calculated. Moreover, ei denoted composite random disturbance term contains two components, vi represents two-dimensional symmetric normally distributed idiosyncratic components $[vi \sim N(0, \sigma^2\ v)]$ and UI is a single-dimensional error component that explains technical inefficiency.

(Aigner et al, 1977) postulate the three types of distributions representing error term; it assumed that every single producer owns a diverse production mechanism for a given combination of inputs. In the case of the exponential distribution, ui is independently, exponentially distributed with $\sigma^2\ v$ and in half-normal distribution ui is independently $N + (0, \sigma^2\ v)$ distributed. In truncated normal distribution situation, the ui is independent $N + (\alpha, \sigma^2\ v)$ distributed with a truncation point at α.

Thus, now from equation (1), we can rewrite the stochastic frontier production function as under;

$$Y_i = f(Xi, \beta)e^{vi} \text{ TE} \quad (3)$$

However, TE represents technical efficiency, when the producer is producing on the production frontier technical efficiency of producer equals one (TE=1) if the technical efficiency is less one (TE<1) then the firm is technically inefficient. As we know that technical efficiency is a measure of the distance of the output observed with reference to the frontier level of output. Thus, the dimension of the technical efficiency can be presented as expressed in equation (4);

$$\mathrm{TE} = \frac{\mathrm{Y_i}}{\mathrm{f(Xi,\beta)e^{vi}}} \quad (4)$$

To find the value of the equation (3), it is imperative to calculate the disturbance term ui , however, it is not observable. In order to get the estimation, we will espouse the (Kumbhakar and Lovell, 2000)

$$E\,(ui/ei) = u*i/\sigma*\{\frac{\phi\left(\frac{u*i}{\sigma*}\right)}{\Phi\left(\frac{u*i}{\sigma*}\right)}\} \quad (5)$$

In equation (4) $\boldsymbol{u*i}$ and $\boldsymbol{\sigma*}$ are depended on the distribution of ui , and $\boldsymbol{\Phi}(.)$ denotes the conventional normal cumulative distribution function while $\boldsymbol{\phi}(.)$ denotes standard normal distribution function.

2.3. Data and Materials

2.3.1. Reliability of instrument

We designed a semi-structured questionnaire for the collection of data from the apple-producing farmers. Items in the questionnaire were included after a systematic review of the related literature. A reliability test of the questionnaire instrument commissioned to gauge the internal consistency in the Stata program prior to data collection from the field. (Nunnally and Bernstein, 2010) suggest a value of 0.70 or greater is suffice at the early phase of research. The outcome of Cronbach’s Alpha test caught a value of scale reliability coefficient 0.88, which finds the questionnaire reliable and consistent.

2.3.2. Study area and data

The districts of Hunza and Nagar are leading apple producers in Gilgit-Baltistan and apple crop contributes substantially to the household income. In order to improve the productivity of apple growers in these districts, the department of agriculture extension Gilgit-Baltistan and JICA (Japan International Cooperation Agency) completed a special program during 2012 and 2017. The sample data for this investigation was gathered from these two districts of Gilgit-Baltistan, where program activities were implemented.

The collected data regarding the apple production, costs of inputs, income from apple production and cost of labor applied, and other indicators related to socio-economic attributes apple growers were included. Statistics about the number of households and other information were obtained from the district administration department to determine the sample size in the area under study. According to information provided by the district administration department, there are 2367 farmers households represent the population in the area under study.

This novelty adopted the random sampling technique to collect the data. Random sampling is the designated most appropriate sampling procedure because each sample has an equal chance of selection (Secker et al., 1995), we adopted Yamane's (1967) random sampling formula to determine the appropriate sample size.

$$n = \frac{N}{1+Ne^2} \quad (6)$$

Whereas n denotes sample size, N represents the total population and e indicates sampling error.

$$n = \frac{2367}{1+2367*(0.07)^2} = 188 \quad (7)$$

A sample of 188 individual apple farmers was determined after estimation adopting the scientific procedure, however, we collected 225 samples from the area under study found appropriate and consistent with the sample size of (Wang et al, 2013).

2.4. Specification of the stochastic frontier model

As we have briefly explained the methods to calculate the technical efficiency in the former part, in order to gauge the technical efficiency of apple growers either the Data Envelopment Analysis (DEA) approach or Stochastic Frontier Analysis (SFA) could have adopted. However, the DEA does not take into consideration due to the essential feature of inconsistency in agricultural production and authenticity of data provided by the apple growers is depends on their memory. On the other hand, SFA is capable of explaining the random shocks and inefficiency component separately while measuring stochastic frontier function unlikely in DEA all deviations from frontier converged due to inefficiency (Bravo-Ureta and Pinheiro, 1997).

Hence, this study espoused the stochastic Frontier Analysis method suggested by (Aigner et al, 1977). In measuring technical efficiency, this investigation adopted the Cobb-Douglas functional form of stochastic frontier due to its feature of simplicity in computation and interpretation of outcomes. Contrary to the former functional form, Translog retains the drawbacks of multicollinearity and degree of freedom (Pavelescu, 2011; Porcelli, 2009).

As we discussed the problems of multicollinearity and degree of freedom, to deal with the concern of heteroscedasticity and to ensure rigor and cogency we transformed the variables into natural logarithms. Consequently, the stochastic frontier model presented in the following mode;

$$lnyi = \ln\{f(xi, \beta)\} + \ln \mu i + \upsilon i \quad (8)$$

The functional, distributional assumptions and the value of other unknown coefficients (βs σs, μ, and v) were measured commissioning the Maximum Likelihood Estimates (MLE) method in the Stata program. MLE approach used to estimate the model because it is more efficient than OLS due to its ability to distinguish the statistical errors from the technical efficiency of the model (Kumbhakar and Lovell, 2010).

As we shed light on details of SFA in previous sections, which consist of two parts; production frontier model and other represents the technical inefficiency model.

$$Lny = LnM + \sum_{i=1}^{10} Ni\ LnXi + V - \mu \quad (9)$$

Whereas Ln denotes natural logarithms, M and N are the unknown parameters of the model while V represents statistical noise and μ denotes inefficiency.

$$Lny = \alpha_* + \alpha_1 + \alpha_2 + \alpha_3 + (v - \mu) \quad (8)$$

$$\mu_i = \delta_* + \sum_{i=1}^{9} \delta iZi \quad (10)$$

The equation (9) represents (Battese and Coelli, 1995) model specifications. The μ_i denote inefficiency which has a positive truncated normal distribution with constant normal parameter. Whereas δi denotes the parameters of coefficients of technical efficiency effect of μ_i while positive and negative signs associated with parameters explains the relationship with farmer's technical efficiency and Zi represented unobserved error term.

$$\mu_i = \alpha_* + \alpha_1 + \alpha_2 + \alpha_3 + \alpha_5 + \alpha_6 + \alpha_7 + \alpha_8 + \alpha_9 \quad (11)$$

$$\mu_i = \alpha_* + \text{Training} + \text{Education} + \text{Technology} + \text{Gender} + \text{Age family head} + \text{Family size} + \text{Fertilizer applied} + \text{Major source of household income} + \text{Farm income}$$

3. Results and Discussions

In this estimation, we adopted a Cobb-Douglas functional form through a single-step estimation procedure of truncated normal distributional form to avoid biases. In this regard, (Kumbhakar and Lovell, 2000; Battese and Coelli, 1995) suggest a single-step procedure in which we incorporated independent variables directly into the inefficiency error term. In this way, we can hypothesize the mean or variance of the inefficiency error term as a function of the explanatory variables.

Table 2: Descriptive statistics of the variables used in stochastic frontier production

Variable	Mean	Std. Dev.	Min	Max
Apple income (PKR)	30770.67	25815.49	4000	157000
Orchard area (Kanal)	3.70	3.41	.5	20
Number of apple trees	18.34	13.73	3	98
Labour cost applied(PKR)	483.66	885.58	1	7200
Training	1.95	.20	1	2
Level of education	3.61	1.52	1	7
Technology	18.24	8.29	9	50
Gender	1.68	.46	1	2
Age of family head	53.54	15.13	20	90
Family Size	6.82	2.98	1	20
Fertilizer cost applied (PKR)	1711.11	1217.64	0	7000
Major Source of household income (PKR)	2.42	1.26	1	4
Farm income (PKR)	102180	84328.08	10000	450000

*Author's own estimations (survey data. 2019), *PKR: Pakistani currency (Rupee),
*Kanal: the unit of measurement (Area)

3.1. Description of variables

The above statistics illustrated in table 2 shows the key variables representing the farm and socio-economic attributes of apple fruit farmers of the area under the empirical examination. A mean income from apple production of 30770.67 PKR noted which ranges from 4000 to 157000 PKR among the apple farmers. An average apple orchard of 3.7 Kanal recorded which spreads from 0.5 Kanal to 20 Kanal with an average of 18 apple trees observed among apple producers. Farmers were asked about their participation in training arranged by the department of agriculture extension under the JICA program.

On average, each farmer participated in approximately eight training related to apple production, orchard management, and marketing. The average level of education among the apple farmers as 8^{th} standard or 8 years of schooling was observed with minimum zero and maximum master-level education. The Agriculture extension services disseminated two types of input technologies i.e. organic fertilizer (Bokashi) and organic pesticide (BSNL), farmers were asked about the application and their impact on quality and quantity of output.

The gender variable represents the distribution of male and female ratio, 68.89% male and 31.11% female farmers were noted at an area under study. The age of the family head variable explains the age directly and experience factor indirectly among the apple farmers, results of this survey observed the mean age of 53.54 years and minimum 20 and maximum of 90 years. The average family size in the area under research is consists of approximately 7 members with a minimum of 1 and a maximum of 20 members. On average one-time fertilizer applied to their orchards during the surveyed season and which cost them on average 1711.11 PKR.

The major source of income represents the principal source of household income, 37.78% agriculture, 12% job, 20.44% business and 29.78% other sources were recorded among the apple farming households. On the other hand; average farm income of 102180 PKR with the range between 10000 PKR and 450000 PKR noted among the apple growers.

Table 3 shows the statistics regarding the stochastic frontier model estimated by using maximum likelihood estimates (MLE). We incorporated three variables to estimate the production frontier model i.e. farm size, number of the apple trees, and labor. The coefficients of production function were positive and noted values of coefficients were significant in defining variation among the apple farmers. The output elasticity of the number of apple trees was 52% that is the largest among the input factors.

Table 3 Estimation of stochastic production function and inefficiency model using maximum likelihood estimates (MLE)

Variables	Coefficients	Standard error	Z
LogY			
Area under apple	.240	.038	6.36***
Number of apple trees	.524	.046	11.46***
Labour	.012	.004	2.79**
_Cons	8.539	.099	85.97***
Technical inefficiency model			

Training attended	-.364	.150	-2.42**
Level of education	. 103	.057	1.82*
Technology	.203	.072	2.79**
Gender	-.264	.083	-3.18**
Age family head	-.156	.080	-1.95**
Family Size	.083	.067	1.23
Fertilizer applied	-.018	.040	-0.47
Major source of household income	-.020	.046	-0.44
Farm income	-.550	.083	-6.61***
_Cons	6.235	.961	6.48***
Usigma			
_Cons	-6.89	2.752	-2.50**
Vsigma			
_Cons	-3.233	.096	-33.50***
sigma_u	.032	.043	0.73
sigma_v	.198	.009	20.72***
lambda	.160	.046	3.46**

Author's own estimations from survey data (2019):
***, **,* Indicates the significance level at 1%, 5% and 10 % respectively.

The positive production elasticities of these factor inputs implied that a rise in the quantity of these inputs would increase apple production. Moreover, a 1% increase in a farm area, number of apple trees and the labor allocated to apple production by the farmer will augment the income from apple production by 0.24%, .52%, and .012% respectively. The sum of these coefficients includes farm size 0.24; the number of apple trees 0.52, and 0.012 labors gave 0.78, which is less than 1, which indicates a constant return to scale production technology. The situation explained afore suggests that apple growers were inefficient in making provision of the input resources consequently led to inefficient production under given production technology.

3.2. Factors affecting technical inefficiency among apple growers

The stochastic frontier analysis is not merely to works as the benchmark against the estimated technical efficiency of producer also identifies the intensity of exogenous factors such as farm, household and socio-economic attributes affecting farmer 's productivity (Kumbhakar and Lovell, 2000).

In this context, this study explored a number of dynamics that influence the technical efficiency of the farmers. Advance knowledge, technique along with the latest technology play a pivotal role in improving farm efficiency. Training is a prime medium of informal education to impart new knowledge and technique to the farmers. In this study, we included the training and technology along with other factors behind the technical inefficiency of apple producers.

The training coefficient was 0.36 with a negative sign, which implied that training tends to reduce the technical inefficiency among the farmers at a 5% significance level. In the end, the prevailing situation suggests that there is an inverse association between trained farmers and technical inefficiency. The result of training coefficient is consistent with the findings of (Huluka and Negatu, 2016) stated that technical efficiency of training graduates was statistical positive and significant in comparison with non-participants, (Lamin et al, 2018) also noted a 10% increase in the technical efficiency of the farmers who participated in training programs.

In this study, the level of education was measured using the years of schooling received by the head of the family. Education is an essential element that enables the farmers to improve their rate of adaptation of new knowledge and technology. The level education coefficient was positive and significant with a value 0.10 at a 10% level of significance as (Shepherd et al, 2017; Fatima et al, 2016) noted similar findings in their empirical studies. The outcome of this factor implied that more educated farmer tends to be less technical inefficient. Maybe the more educated farmer concentrates on other sources of income and livelihood e.g. job and business rather than apple farming. Or maybe due to shrinking of already relatively small landholdings in the focused area.

The technology was significant at a 5% significance level with a positive coefficient value .20 which exhibits the affirmative connection between technology and technical inefficiency of apple farmers. Similarly, propositions postulated by (Torkamani and Hardakar, 1996) if the existing knowledge is not efficient, the introduction of new technology may not produce desired impacts. Improved efficiency is crucial for rising productivity and shifting on new technology meaningless until the existing technology is utilized at the maximum level (Kalirajan et al, 1996).

The coefficient of gender found significant with a negative value of 0.26 at a 5% level of significance. This condition implied that gender tends to decline the technical inefficiency of apple farmers in an area under research, the findings of this coefficient in line with findings of (Mukwalikuli, 2018).

The coefficient age of family head was negative coefficient with a value of 0.15 at a 5% significant level which shows an adverse relation between family head age and technical inefficiency. Similarly, the finding of the age of the family head coefficient coordinates with the results of (Bäckman et al, 2011). Family size is a pivotal attribute of rural households in developing economies. The coefficient of family size was positive with a value 0.083 and found significant. This outcome inferred that an additional one unit of family member source of the technical inefficiency among the apple farmers.

The coefficient of fertilizer cost is negative with a value of 0.018 and found insignificant while this situation implied adverse linkage between the cost of fertilizer and technical inefficiency of apple grower however the coefficient found statistically insignificant and as (Effendy et al, 2019) postulated similar sort of outcomes in their empirical study. The major source of income provides information regarding the key source of household income. The coefficient of MSI was insignificant and negative with a value of 0.02, which implied that the coefficient tends to reduce technical inefficiency among apple farmers.

The fundamental objective of farm activities is to generate income and cater to the needs of farm households. The coefficient of farm income was a negative value of 0.55 and at a 1% level of significance, which has been the most influential factor affecting the technical inefficiency among the farmers in the study area. Farm income and farm productivity are interdependent factors if output increases this would enhance the farm income and ultimately affects the technical efficiency (Penda and Asogwa, 2011).

3.3. Range and dispersion of technical efficiency

The range of technical efficiency scores between .43 minimum and .99 maximum with average technical efficiency of .92 were detected among apple farmers in the area under consideration. The mean value of technical efficiency suggests that each farmer’s production efficiency level observed at 92% with existing inputs and production technology. Former perceived circumstances suggest that 8% of technical inefficiency differential could be bridged by improving the technical management at the farm level.

Table 4: Range and dispersion of Technical Efficiency

Range	Frequency	Percentage
.40-.50	3	1.34
.51-.60	5	2.23
.61-.70	14	6.25
.71-.80	18	8.04
.81-90	20	8.93
.91-1.0	164	73.21
Total	224	100%
Mean	0.92	
Minimum	0.43	
Maximum	.99	

Source: Author's own estimations (survey data. 2019)

3.4. Dispersion of technical efficiency

Statistics illustrated in table 4 represent the dispersion of estimated technical efficiency among the apple farmers**.** The 1.3 % of farmers fall in between the efficiency score of 0.40 and 0.50 and 2.23% of farmers were in between the technical efficiency score of 0.51 and 0.60. Whereas the remaining 6.25% of apple farmers had, technical efficiency score ranged between 0.61 and 0.70 and approximately 8% fall were between 0.71 and 0.8.

On the other hand, 8.93% and 73.21% of farmers were under the efficiency score range of 0.81-0.90 and 0.91-1 respectively. An average technical efficiency score was 0.92 and spreads of efficiency score range 0.43 and 0.99 noted among the sampled farmers. Differentials in efficiency scores suggest that growers in the area under research were not able to utilize their resources properly to attain the maximum level of production due to inefficiency.

4. Conclusions and Policy Remarks

The essential objective of this investigation was to assess the technical efficiency and to point out the contributions of training and technology along with other factors towards technical inefficiency among the apple growers in Gilgit-Baltistan Pakistan. The range of technical efficiency scores between 0.43 minimum and 0.99 maximum with average technical efficiency of 0.92 observed among apple farmers in the area under consideration.

The mean value of technical efficiency suggests that each farmer's production efficiency level was at 0.92 with existing inputs and production technology Differentials in efficiency scores suggest that apple growers in the observed area were not 100% technical efficient due to inefficiency. This condition suggests that there would be possibilities to enhance the apple income by 8% engaging the existing combination of inputs and production technology.

In order to gauge the level of return to scale (RTS), we have calculated RTS value 0.78 <1 for the whole sample which implied that apple farmers were operating under constant return to scale regime. Consequently, keeping other inputs constant, 1% increases in all inputs yields less than a unit increase in apple output. Furthermore, if in case apple farmers expand their farm operations would confront a constant return to scale. On the other hand, the inefficiency model exhibits an inverse relationship among inefficiency and training, gender, family head age, cost of fertilizer applied, major source household income and farm income, which implied that these factors tend to reduce the technical inefficiency.

While other factors i.e. education, technology, and family size tend to raise technical inefficiency among apple farmers. This study has brought out the number of issues affecting the productivity and efficiency of apple growers in the area under consideration. As the study noted, training affects technical inefficiency leads to decrease inefficiency while the technology showed a positive influence on technical inefficiency among the apple farmers. Technical efficiency and management of apple farms can be improved by strengthening the capacities of farmers. In order to eliminate inefficiency and to accelerate productivity growth, a comprehensive relevant technology transfer that compatible with local knowledge and environment is suggested.

Production technologies are playing a pivotal role in expanding production, dissemination, and transfer of new production technology can make a difference in boosting apple production. Therefore, the provision of technology, training and extension services to the apple farmers, which would enable them to utilize their inputs efficiently to maximize apple output and income ultimately. The results of this investigation will pave the strategic pathways for the policymakers to revisit the existing policy regime and design the growth-oriented policies that will ultimately improve the efficiency and productivity of the not only specified farmers and others as well.

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6. Acknowledgement

This study was supported by the National Natural Sciences Foundation of China (Grant No. 71673215, No.71974158). We would like to extend our gratitude to all respondent farmers for their valuable time and cooperation.