Technical efficiency of cotton farms and its determinants: application of Stochastic Frontier Analysis

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Abstract

Efficient use of scarce resources is an important issue for countries and sectors. This study uses farm level data to investigate the technical efficiency and its determinants for a sample of 80 cotton farms using the translog stochastic frontier analysis. The mean technical efficiency of the farms was found to be 86.8% indicating that about 13.2% of output level is lost to technical inefficiency. This implies that a potential exists to increase cotton production through improved efficiency in the research area. Technical inefficiency was modelled as a function of farm specific variables. The main determinants of technical efficiency include farmer's age, farm size, farmer's experience and non-farm income. The variables of farm size and farmer's experince negatively affected technical inefficiency. As farm size and farmers' experience increased technical inefficency decreased. However, farmer's age and non-farm income showed positive relationship with inefficiency. In the light of these findings, new agricultural policies should be designed to increase technical efficiency of cotton farms. Agricultural policies that will be implemented to improve the technical efficiency of cotton farms will also create an opportunity to increase the profitability and sustainability of the farms.

Keywords: Efficiency. Agriculture. SFA. Cotton Farms. Turkey.

1. Introduction

Agriculture has a vital role which provides livelihoods to large population and is an important driver for growth and to reduce poverty in Turkey. Cotton one of the basic products in Turkish agriculture, is a product of great economic importance with its widespread and compulsory use, the added value and employment opportunities it creates.

Cotton provides important contributions to the country's economy due to its many areas of use in textile, garment industry, vegetable oil, feed industry etc. Especially Turkish textile industry, whose basic raw material is cotton, is an indispensable sector for the country's economy in terms of both exports and employment with the added value it provides. Therefore, it is necessary to increase cotton production in Turkey for the continuation of the success of the textile industry in exports and employment.

In Turkey cotton is cultivated mainly in four regions; Aegean, Çukurova, Southeast Anatolia and the Mediterranean. As of 2019, the amount of cotton acreage and production in Turkey decreased to 478 000 ha and 2.2 million tonnes respectively compared to the previous year. 84% of the cotton grown in Turkey has been produced mainly in Sanliurfa (37%), Aydin (11%), Diyarbakır (11%), Hatay (10%), Adana (9%) and Izmir (6%) provinces (MAF, 2020).

In Turkey, because of the decrease in cotton production through the years and the development of the textile industry, the consumption rate of cotton could not be met with domestic production and this issue caused an increase in cotton import. Cotton imports were 766 647 tons in 2018 and 950 590 tons in 2019. Turkey's top cotton imports have been mad from the US, Brazil and Greece (MAF, 2020).

Turkey is faced with many fundamental issues, such as productivity and efficient use of resources in agriculture. Increasing efficiency is possible by using existing resources rationally and utilizing modern technology. Efficiency analyzes to be made in the agricultural sector can guide the policies to be established for the effective use of production factors.

Considering the importance of cotton as an agricultural product for Turkey, to determine the technical efficiencies of cotton farms is importatnt in terms of optimum use of resources and determining strategies for the future. Measures that will be taken to improve the technical efficiency of cotton farms will also create an opportunity to increase the profitability and sustainability of these farms.

Technical efficiency measures the relative ability of the farmers to get the maximum possible output at a given level of input or set of inputs. Technically efficient farmers are those that operate on the production frontier which represents maximum output attainable from each input level. All feasible points below the frontier are technically inefficient points (Asefa, 2011).

There are two main competing methods for analyzing technical efficiency and its principal determinants: the non-parametric frontier and the parametric frontier.

One of the most widely used methods among nonparametric methods is Data Envelopment Analysis (DEA) method developed by Charnes, Cooper and Rhodes (1978). Among the parametric methods, the most used ones are; Regression Analysis and Stochastic Frontier Analysis (SFA). Stochastic Frontier Analysis was developed by Aigner, Lovell and Schmidt (1977), Meusen and Van Den Broeck (1977). Mathematical linear programming is used for the estimation of data envelopment analysis (DEA) while stochastic frontier analysis is commonly based on econometric procedures (Khan and Ullah, 2020).

DEA suffers from the criticism that it takes no account of the possible influence of random shocks like measurement errors and other noises in the data (Coelli, 1995). DEA assumes all deviations from frontier to be inefficiency. However, there are many factors affecting the variability in production amount in agriculture (Mailena et al. 2014). Due to these criticisms of DEA Stochastic boundary analysis is widely used in efficiency evaluations in agriculture.

The main aim of this study is to assess the technical efficiency of cotton farms in Turkey by using the stochastic frontier approach. This study also explains determinants of technical efficiency such as age, experience, education, farm size etc.

According to the results of the technical efficiency analysis, some suggestions will be made in order to enhance cotton production in Turkey.

2. Literature Review

Efficiency has drawn more attention from researchers in recent years. There are many studies measuring efficiency for many products in agriculture. Most of the research in the literature applies data envelopment analysis (DEA) to measure efficiency for different agricultural products such as wheat, paddy, rice, vegatable, banana, hazelnut, cotton, etc. Few of the empirical studies conducted have measured farm level technical efficiency by using Stochastic Frontier Analysis (Battese and Broca, 1997; Chakraborty et al., 2002; Chiang et al., 2004; Hassan and Ahmad, 2005; Madau, 2011; Bäckman et al., 2011; Theriault, 2011; Ghee-Thean, 2012; Çobanoğlu, 2013; Mailena et al., 2014; Hossain et al., 2015; Abdul-

Rahaman, 2016; Fatima et al., 2016; Abdulai et al., 2017; Umar et al., 2017; Bala et al., 2018; Ali and Kpakpabia, 2019; Bambe, 2019; Tasila Konja et al., 2019).

Some of the studies determining the technical efficiency in cotton farms using the SFA method are summarized below.

Chakraborty et al. (2002) have focused on technical efficiency in cotton farming. In this study, technical efficiency for cotton growers was examined using both stochastic (SFA) and nonstochastic (DEA) production function approaches. On average, irrigated and nonirrigated farms were found to be 80% and 70% efficient, respectively.

Çobanoğlu (2013) conducted a study to estimate technical efficiency scores based on DEA and SFA and compared these two frontier methods results. The mean efficiency measure (0.91) obtained from the stochastic frontier was found higher than the measures calculated from the VRS DEA (0.77) and CRS DEA (0.25).

Solakoglu et al. (2013) conducted a study to measure the technical efficiency of cotton production incorporating the effect of premium payments to farmers by using cobb-douglas stochastic frontier model. The mean efficiency was estimated, by using panel data, around 65% for cotton production when 8 years and 14 cities were taken into account. The premium payments found to be the most important determinant of inefficiencies.

Abdul-Rahaman (2016) analyzed technical efficiency of smallholder cotton farmers in three selected districts of the Northern Region of Ghana using stochastic frontier production function approach. The results showed that the technical efficiency of smallholder cotton farmers in the area ranges between 16.05% and 98.13% with mean efficiency score of 84.5%.

Fatima et al. (2016) conducted a study to estimate technical efficiency of Non-BT and BT cotton farms by using SFA. The Cobb-Douglas Stochastic Frontier Analysis (SFA) has been employed to determine the technical efficiency of farmers. The estimated mean technical efficiency of NonBT cotton farmers has been found to be 0.70, and 0.90 is the technical efficiency found in that of the BT cotton farmers.

Bala et al. (2018) conducted a study, based on Stochastic Frontier Profit Function that assumed Cobb-Douglass specification form, a multiple regression model was estimated using a cross-sectional data. According to the analysis, the profit efficiency of the producers was found to be between 67.1% and 98.1%.

Ali and Kpakpabia (2019) conducted a study to determine the level of technical efficiency of cotton producers and analyse its determinants by using SFA in Togo. The results showed that the average technical efficiency of cotton producers was 48.33%. It was therefore possible to increase the level of cotton production to 51.67% using the available resources.

3. Material and Methods

3.1. Stochastic Frontier model

The stochastic frontier model was developed by Aigner et al. (1977), and Meeusen and van den Broeck (1977) building on previous work done by Farrell (1957) as well as Aigner and Chu (1968).

The Stochastic Frontier Production Function is more appropriate for measuring technical efficiency because it overcomes the inadequate characteristics of the assumed error term in conventional production functions which have limitations on statistical inference of the parameters and the resulting efficiency estimates (Islam et al., 2016).

The biggest advantage of stochastic frontier model is the introduction of stochastic random noises that are beyond the control of the farmers in addition to the inefficiency effects (Battese and Coelli, 1995). The stochastic frontier model decomposes the error term into a two-sided random error that captures random effects outside the control of the farmer and the one-sided inefficiency component. According to Coelli et al. (1998), it is called a stochastic function because the output values are bounded by the stochastic (random) variable $exp(X_i\beta+V_i)$. Furthermore, the random error V_i can be positive or negative and therefore the stochastic frontier outputs vary about the deterministic part of the model, $exp(X_i\beta)$.

The general stochastic model is given as:

$$Y_i = f(X_i\beta)exp(V_i - U_i)$$

Where, Y_i denotes the output fort he *i*th farm (i=1,2,….n); X_i is a (1 x k) vector of factor inputs of the *i*th farm, and β is a (1 x k) vector of unknown parameters to be estimated; V_i is a random variable which is assumed to be normally, independently and identically distributed { N $(0,\sigma_v^2)$}. The term Ui is a non negative random variable which accounts for pure technical inefficiency in production and is assumed to be independently distributed (Aigner et al., 1977). The assumption of the independent distribution between Ui and Vi allows the separation of the stochastic and inefficiency effects in the model (Islam et al., 2016).

$Y = f(X_i\beta)$and $exp(V_i - U_i)$ show the deterministic and stochastic parts of the production frontier, respectively.

The production inefficiency Ui can be specified as:

$$U_i = Z_i\delta + W_i$$

where Z_i is a (p x 1) vector of explanatory variables which may influence the efficiency of the ith farm; and δ is an (1 x p) vector of parameters to be estimated; an the W_i's are unobservable random variables, which are assumed to be independently distrubuted with mean zero and unknown variance σ^2, such that U_i is non-negative, i.e. $W_i \geq - Z_i\delta$.

With given the input vector, Xi, the potential output is defined by the frontier function, $Y^* = exp(X_i\beta + V_i)$. The farm level technical efficiency of production for the ith farm (TEi) is defined as:

$$TE_i = Y_i / Y_i^* = \frac{Y_i}{\exp(X_i\beta + V_i)} = \exp(-U_i)$$

The maximum likelihood (ML) estimation technique is used to simultaneously estimate the parameters of the stochastic frontier and the technical inefficiency model. The parameters include β's and the variance parameters $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2/\sigma^2$ (Battese and Corra, 1977), where σ^2 is the sum of the error variance, γ has a value between zero and one, measures the total variation of output from the frontier that attributed to the existence of random noise or inefficiency. Inefficiency is not present when γ =0 which means that all deviations from the frontier are due to random noise. However, if γ = 1 then the deviations are completely caused by inefficiency effects (Battese and Coelli, 1995). The computer program, FRONTIER Version 4.1, is used to obtain the ML estimates for the parameters of this model.

The stochastic frontier to estimate efficiency is a very relevant instrument for productivity growth, especially for a country that yearns to structure and develop its agricultural sector (Ali and Chaudhry, 1990).

3.2. Empirical model specification

The stochastic frontier approach requires a prior specification of the most widely used functional forms like Cobb-Douglas and Translog. Cobb-Douglas is a special form of the translog production function where the coefficients of the squared and interaction terms of input variables of translog frontier are assumed to be zero (Asefa, 2011).

In this study, the maximum likelihood (ML) estimation technique was used to estimate the parameters of stochastic frontier. The explanatory variables used to explain inefficiency were included in the model when estimating the measures of technical efficiency. The results of the maximum likelihood ratio-type test, used to test the translog against Cobb-Douglas, showed that translog production frontier was an appropriate model for our data.

The empirical version of the model presumes a translog production frontier:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ji} + \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{jk} \ln X_{ji} \ln X_{ki} + v_i - u_i$$

where Y_i indicates the average unginned cotton yield (kg/ha), X_1 represents the the total fertiliser costs (US $/ha), X_2, X_3, X_4 and X_5 represent the costs of chemicals, irrigation, labour and machinery per hectare respectively during the growing season.

Table 1 presents the descriptive statistics of cotton yields, inputs, and the explanatory variables used in the analysis.

The identification of the variables that influence the level of technical efficiency is a particularly valuable for policy makers. The empirical farm specific variables associated with technical inefficiency as in $(U_i = Z_i\delta + W_i)$ are shown in Table 1. The variables of Z_1 = farm size (ha); Z_2 =age (year); Z_3 = experience (year); and Z_4 = non-farm income.

The coefficients of the translog production function in SFA were estimated by employing Frontier Program Version 4.1 (Coelli, 1996). There are a number of null hypotheses for the SFA approach that will be tested such as the validation of the Translog production function, the absence of inefficiency effects and the absence of stochastic inefficiency effects. The results of various hypotheses tested in the analysis are presented in Table 2. A likelihood-ratio test (LR test) is used to test these hypotheses, which can be conducted as follows:

$$\lambda = -2\{Ln[L(H_0)] - Ln[L(H_1)]\}$$

where $L(H_0)$ and $L(H_1)$ denote the values of likelihood function under the null *(H_0)* and alternative *(H_1)* hypotheses, respectively. The value of λ is compared with the critical value of chi-square from the table in Kodde and Palm (1986).

3.3. Data collection

Cotton production in Turkey is concentrated mainly in four regions. Among these four regions, the region with the highest cotton production is the Southeastern Anatolia region. Şanlıurfa is located in this region and produces the 37% of the cotton grown in Turkey. Therefore, this study was conducted in Şanlıurfa province of the south-east Anatolian region. Data for the study were obtained from 80 cotton farmers who were randomly selected.

Table 1: Variable definitions and summary statistics for the empirical model

Variable Name	Definition	Measurement	Summary Statistics			
			Mean	SD	Min	Max
Output and input variables						
Y	Unginned Cotton Yield	Kg/ha	4995	799.11	2 500	6 500
X_1	Fertiliser costs	US $/ha	257.41	57.75	98.01	381.50
X_2	Pesticide costs	US $/ha	214.91	74.43	109.40	427.54
X_3	Irrigation costs	US $/ha	654.16	235.16	316.52	1169.55
X_4	Labour costs	US $/ha	395.34	220.01	49.17	1254.29
X_5	Machinery costs	US $/ha	506.26	221.74	80.68	1003.79
Farm specific variables						
Z_1	Farm size	ha	10.82	5.95	4	30
Z_2	Age	year	42.39	7.26	32	73
Z_3	Experience	year	13.59	4.62	5	30
Z_4	Non-farm income	Dummy (1=yes, 0=no)	0.22	0.42	0	1

Data on farm inputs and output were obtained by using face-to-face interviews through a structured questionnaire in 2018/2019 production period.

The output and input variables needed for the efficiency analysis and descriptive statistics for the inputs and outputs assessed in the models are summarized in Table 1. Cotton yield (kg/ha) has been taken into consideration as the output. The difference in yields refers to yield gap which arises due to inefficiency (technical allocative or both) in cotton cultivation. A number of studies on technical efficiencies of crop production have pointed out the existence of yield gap (Kumar et al., 2019). Five inputs were included in the estimation of the frontier production function. These inputs were the most important expense items in cotton production, which are irrigation, machinery, labor, fertilizer and pesticide costs, respectively. The selected variables were similar with previous studies (Gül et al., 2009; Bäckman et al., 2011; Ghee-Thean et al., 2012; Çobanoğlu, 2013; Mailena et al., 2014; Hossain et al., 2015; Abdulai et al,. 2017; Bambe et al., 2019).

The average yield of unginned cotton in the sample was approximately 4995 kilograms per hectare with a large standard deviation (799.11 kilograms per hectare). The main reason for the high irrigation costs, which is calculated as 654.16 US $/ha on average, is the high electricity costs for irrigation. The average machinery costs per hectare was 506.26 US $ ranging from 80.68 to 1003.79 US $. The reason for this variation was that some farms preferred to harvest only by using labor force and some farms preferred only to harvest with machinery. The average costs for fertiliser and pesticide per hectare were 257.41 and 214.91 US $, respectively.

Some of the socio-economic variables commonly used in previous studies to explain technical inefficiency were farm size, farmers' age, experience and existence of non-farm income (Bozoğlu and Ceyhan, 2007; Bäckman et al., 2011; Ghee-Thean et al., 2012; Mailena et al., 2014; Hossain et al., 2015; Islam et al., 2016; Abdul-Rahaman, 2016; Umar et al., 2017; Ali and Kpakpabia, 2019; Tasila Konja et al., 2019). Farm size was included as hectares in order to reveal the relationship between farm size and technical efficiency. The age variable included in the inefficiency model is used to test if younger farmers were more innovative to test that younger farmers were more innovative. Experience variable was included also to reveal if lack of experience effect technical inefficiency. To explore the relationship between technical efficiency and the existence of non-farm income, the non-farm income variable was a dummy (1= non-farm income, 0 =otherwise).

4. Results and Discussion

Table 3 shows the maximum likelihood estimates of the estimated stochastic frontier production function and the determinants of technical efficiency.

In order to select the most appropriate functional form which adequately represents the data, both Cobb-Douglas and Translog frontiers are estimated using likelihood ratio test. Therefore, the first hypothesis testing is choosing the appropriate functional form for the data from the Cobb-Douglas and Translog frontier (Table 2). The hypothesis conformed that Cobb-Douglas production function was not suitable for analysis. Based on the likelihood ratio which was 45.26 and was higher than the critical value, the null hypothesis was rejected. The functional form of the stochastic frontier was determined by testing the adequacy of the Translog relative to the Cobb-Douglas.

The second hypothesis tests the existence of the inefficiency factor. The null hypothesis was $H_0 = \gamma = 0 = \delta_0 = \delta_1 = \cdots = \delta_4 = 0$ and the likelihood ratio test indicated that the null hypothesis rejected. It implied the existence of inefficiency across the cotton farms.

The third hypothesis tests for the presence of stochastic inefficiency. The null hypothesis is $H_0 = \gamma = 0$ that specifies the technical inefficiency effects are not stochastic. The test result rejected the null hypothesis, implying that the traditional average response function was not an adequate representation of the data.

Table 2: Generalized likelihood ratio test

Null hypothesis	Test Statistic (λ)	Critical Value*	Decision
The Translog SFPF can be reduced to a Cobb – Doglass SFPF			
$H_0 = \beta_{jk} = 0$	45.26	24.38	Reject H_0
No inefficiency effects			
$H_0 = \gamma = 0 = \delta_0 = \delta_1 = \cdots = \delta_4 = 0$	33.56	11.91	Reject H_0
Non stochastic inefficiency			
$H_0 = \gamma = 0$	33.43	2.71	Reject H_0

*Critical value ($\square^2_{0.05}$) obtained from Kodde and Palm (1986).

The mean technical efficiency of cotton farmers was estimated at 86.8% (table 3). It ranged between 56.1% to 99.9%. This indicates that if cotton farmers use their existing level of inputs in an efficient manner, output on average can be increased by 13.2%. Cotton farmers in the research area can improve their technical efficiency by fully utilizing their existing inputs and technology.

The variance parameters of the model was significantly different from zero at the 1% level. The value of 0.999 of the gamma (γ) for the production function suggesting that technical inefficiency had significant effect on output. This means that 99.9% of the total variation in output was as a result of factors within the control of the farmer and that variation in cotton production per hectare could be attributed to inefficiency. The remaining 0.01% was due to factors outside the control of the farmers. The value of gamma reveals the fact that most farmers in the study area are using their existing resources inefficiently.

The sigma squared value of 0.0337 was significantly different from zero at 1% and indicated the correctness of the specified distributional assumption for the inefficiency term.

Six β coefficients are significant at the 1% level, one at the 5% level, and two at the 10% level, suggesting that the model is a good fit. The study shows that pesticide, irrigation and machinery significantly affect the level of cotton output in the study area.

The output elasticity of each input cannot be obtained directly from Translog production function like it can be obtained using Cobb-Douglas production function. The traditional elasticity of the output with respect to the k^{th} input indicated the formula from Battese and Broca (1997) is as follows:

$$\eta_k = \beta_k + 2\beta_{kk} lnX_{ki} + \sum_{j \neq k} \beta_{kj} lnX_{ji}$$

Output elasticity is defined as the percentage change in output from a 1% change of all input factors. The returns to scale is calculated by summing up all the output elasticity of inputs. When retuns to scale is greater than one, there are increasing returns to scale for the farms (Chiang et al., 2004).

The elasticities of output for fertilizer, pesticide, irrigation, labour, machinery and returns to scale elasticity of the translog stochastic frontier model are given in Table 4. The highest output elasticity is for pesticide, 5.88, implying that a 1% increase of pesticide cost, *ceteris paribus*, will increase production by 5.88%. This indicates that pesticide as an input has a major positive effect on output, followed by irrigation (1.06).

Table 3: Maximum likelihood estimates of translog stochastic frontier

Variable	Parameter	Coefficients	t-ratio
Stochastic Frontier Model			
Constant	β_0	10.7017*	10.990
Fertiliser	β_1	0.5879	0.6583
Pesticide	β_2	-8.2267*	-9.1529
Irrigation	β_3	-1.3352***	-1.7153
Labour	β_4	0.9311	1.1846
Machinery	β_5	4.1067*	4.6439
Fertiliser x Fertiliser	β_6	0.3053	0.9699
Fertiliser x Pesticide	β_7	0.4016	1.3037
Fertiliser x Irrigation	β_8	-0.1191	-0.3612
Fertiliser x Labour	β_9	-0.4497**	-2.5067
Fertiliser x Machinery	β_{10}	-0.5050	-1.5228
Pesticide x Pesticide	β_{11}	0.6673*	5.2144
Pesticide x Irrigation	β_{12}	0.8634*	6.0843
Pesticide x Labour	β_{13}	0.1204	0.6057
Pesticide x Machinery	β_{14}	-0.2372	-1.5391
Irrigation x Irrigation	β_{15}	0.0219	0.2602
Irrigation x Labour	β_{16}	-0.2256	-1.4298
Irrigation x Machinery	β_{17}	-0.0830	-0.8996
Labour x Labour	β_{18}	0.1706*	4.339
Labour x Machinery	β_{19}	0.0364	0.3674
Machinery x Machinery	β_{20}	-0.1981***	-1.7017
Technical inefficiency model			

Constant	δ_0	-0.2074	-0.5244
Farm Size	δ_1	-0.0014**	-2.0733
Age	δ_2	0.0139***	1.8587
Experience	δ_3	-0.0221**	-2.0547
Non-farm income	δ_4	0.2802*	2.6588
Variance parameters			
Sigma-square	$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.0337*	6.9848
Gamma	γ	0.999*	21048.7
Log likelihood		54.0886	

Estimates are significant at *1%, ** 5%, *** 10%.

The elasticity of output for machinery, fertiliser and labour has a negative effect on cotton production, -2.67, -0.36 and -0.16, respectively. The sum of all output elasticities is 3.76, indicating that on average the cotton farms examined has increasing returns to scale. In other words, if the industry increased all factor inputs by 1%, cotton production would increase by only 3.76%.

Table 3 also shows the results explaining the determinants of technical inefficiency in cotton production. Assessing determinants of technical inefficiency is as important as calculating technical efficiency scores for making agricultural policy to reduce resource waste and improve farmers' livelihoods. From the result, farm size, age, experience and non-farm income were significant variables of technical inefficient in the study area. The positive signs of the estimates for these variables indicate that there is an increase technical inefficiency. A negative estimate indicates a positive effect on technical efficiency.

Farm size was a significant determinant of the technical efficiency of cotton farms. The coefficient is negative and statistically significant at 5%, and implies that farms with relatively large of arable land tend to be more efficient. This result is consistent with previous studies (Wadud and White, 2000; Tipi et al., 2009; Karimov, 2014; Mango et al., 2015; Tenaye, 2020).

The age of farmers was significant at 10% and showed a positive relationship with technical inefficiency in cotton production. The age coefficient (0.0139) indicated that the younger farmers were more efficient than the older ones. This finding is consistent with previous studies (Battese and Coelli, 1995; Bozoğlu and Ceyhan, 2007; Bäckman et al., 2011; Ghee-Thean et al., 2012; Mailena et al., 2014; Olatidoye et al., 2018).

Table 4: Output elasticities of the translog model

Input	Elasticity
Fertiliser	-0.356
Pesticide	5.883
Irrigation	1.060
Labour	-0.157
Machinery	-2.673
Returns to Scale	3.756

The negative estimate for the experience of farmers implied that the number of years in cotton farming led to better managerial skills being acquired over the years. An increase in farming experience provides better knowledge about the production environment in which decisions are made. This finding is also consistent with previous studies (Sharma and Leung, 1998; Bozoğlu and Ceyhan, 2007; Bäckman et al., 2011; Abdul-Rahaman, 2016; Islam et al., 2016; Umar and Yakubu, 2017; Abdulai et al., 2017; Olatidoye et al., 2018; Ali and Kpakpabia, 2019).

Another outcome of the inefficiency model was that the positive and significant effect of non-farm income on technical inefficiency implied that existence of non-farm income enhanced the technical inefficiency of the cotton farms. This is because farmers may allocate more of their time to non-farm activities and thus may lag in agricultural activities or neglect the farm activities. This finding is consistent with previous studies (Bozoğlu and Ceyhan, 2007; Tipi et al., 2009; Asefa, 2011; Bäckman et al., 2011; Karimov, 2014; Tenaye, 2020).

5. Conclusions

This study has applied both the stochastic frontier production function and technical inefficiency effects model to analyse the technical efficiency of cotton farms in the research area. The analysis show that the translog stochastic frontier production function model fits the data better than the Cobb –Douglas.

The empirical findings show that the predicted efficiencies vary widely among the sample cotton farms with a mean technical efficiency value of 86.8 %. The variation in technical efficiency implied that most of the farmers are still using their resources inefficiently in the production process and there still exists opportunities for increasing their cotton production by improving their current level of technical efficiency. Cotton yield per hectare can be increased by 13.2% at the existing level of inputs and current technology by operating at full technical efficient level.

The value of 0.999 of the gamma (γ) for the production function suggesting that technical inefficiency had significant effect on output among the sampled farms.

Farm level specific variables were used to explore inefficiency determinants. The sign of coefficients of variables have been as the expected. Increasing farmer's experience and farm size were found to enhance technical efficiency. In contrast, farmer's age and existing of non-farm income were found to decrease technical efficiency. The findings suggest that farms managed by younger farmers appear to be more technically efficient. Agricultural policies should be developed to prevent migration of the young population from countryside and to motivate young population for agricultural production.

In order to enhance experience of farmers through farm level extension and training activites should be organized. Policy makers should focus on enhancing farmers' access to information via the provision of better extension services and farmer training programs.

Continuous improvement in the technical efficiency of cotton production could promote income growth, prevent migration and reduce poverty. Therefore, technical efficiency studies in cotton should be carried out continuously to design new agricultural policies for improving efficiency.

This research has some limitations because of the deficiencies in regular record keeping at the farm level in Turkey. Most of farmers interviewed only tried to remember information about input usage. As stated in previous studies (Çobanoğlu, 2013; Armağan and Nizam, 2012), supporting sufficient and regular records on cotton farms may be invaluable for optimum input and output management and to enhance efficiency at the farm level.

6. References

ABDUL-RAHAMAN, A. Stochastic frontier analysis (SFA) of technical efficiency, insights from smallholder cotton farmers in the Northern Region of Ghana. *Global Journal of Agricultural Economics, Extension and Rural Development*, v.4, n.1, p.361-367, 2016.

ABDULAI, S.; NKEGBE, P.K.; DONKOR, S.A. Assessing the Economic Efficiency of Maize Production in Northern Ghana. *Ghana Journal of Development Studies*, Vol. 14, No. 1, May, 2017.

AIGNER, D.J.; CHU, S.F. On estimating the industry production function. *American Economic Review*, v. 58, n. 4, p. 826 – 839, 1968.

AIGNER, D.J.; LOVELL, C.A.K.; SCHMIDT, P. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics*, v. 6, p. 21-37, 1977.

ALI, M.; CHAUDHRY, M.A. Inter-regional Farm Efficiency in Pakistan's Punjab: A Frontier Production Function Models. *Journal of Econometrics,* v. 6, p. 21-37, 1990.

ALI, E.; KPAKPABIA, K.T. Determinants Of Technical Efficiency Of Cotton Farmers In Togo, *Review of Agricultural and Applied Economics* (RAAE), v. 22, n. 2, number 293651. 2019.

ARMAĞAN, G.; NİZAM, S. Productivity and efficiency scores of dairy farms: the case of Turkey. *Quality and Quantity*, v. 46, p 351–358, 2012.

ASEFA, S. Analysis of technical efficiency of crop producing smallholder farmers in Tigray, Ethiopia. *MPRA Paper (40461*), (https://mpra.ub.uni-muenchen.de/40461/), 2011.

BÄCKMAN, S.; ISLAM, K.M.Z.; SUMELIUS, J. Determinants of Technical Efficiency of Rice Farms in North-Central and North-Western Regions in Bangladesh. *The Journal of Developing Areas*, v.45, n. 1, 2011.

BALA, M.; SHAMSUDIN, M.N.; RADAM, A.; LATIF, I.A. Profit Efficiency among Cotton Farmers: A Cobb-Douglass Stochastic Frontier Production Function Analysis. *Journal of Asian Scientific Research*, v. 8, n. 7, p. 237-246, 2018.

BAMBE, E.H.K.; NTOTO, R.; WEI, X.W. Stochastic Frontier Model and Factors Influencing Seed Cotton Production Cost. *London Journal of Research in Science: Natural and Formal*, v.19, n. 5, 2019.

BATTESE, G.E.; BROCA, S.S. Functional forms of Stochastic Frontier Production Functions and models for technical inefficiency effects: a comparative study for wheat farmers in Pakistan. *Journal of Productivity Analysis*, v. 8, pp 395–414, 1997.

BATTESE, G.E.; CORRA, G.S. Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia. *Australian Journal of Agricultural Economics*, v. 21, p. 169-179, 1977.

BATTESE, G.E.; COELLI, T.J. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, v. 20,p. 325- 332, 1995.

BOZOĞLU, M.; CEYHAN, V. Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun Province, Turkey. *Agricultural Systems*, v. 94, p. 649–56, 2007.

CHAKRABORTY, K.; MISRA, S.; JOHNSON, P. Cotton farmers' technical efficiency: stochastic and nonstochastic production function approaches. *Agricultural and Resource Economics Review*, v. 31, p. 211–220, 2002.

CHARNES, A.; COOPER, W.W.; RHODES, E. Measuring the inefficiency of decision making unit. *European Journal of Operational Research*, v. 2, p. 429–44, 1978.

CHIANG, F.; SUN, C.; YU, J. Technical efficiency analysis of milkfish (Chanos chanos) production in Taiwan - an application of the stochastic frontier production function. *Aquaculture*, v. 230, p. 1–4, 2004.

COELLI, T.J. Estimators and Hypothesis Tests for Stochastic Frontier Function: A Monte Carlo Analysis. *Journal of Productivity Analysis*, v. 6, p. 247 – 268, 1995.

COELLI, T.J. A Guide to Frontier Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation, *Working Paper No 96/07*, Center for Efficiency and Productivity Analysis, Department of Econometrics, University of New England, Armidale, NSW, 1996.

COELLI, T.J.; RAO, D.S.P.; BATTESE, G.E. An Introduction to Efficiency & Productivity Analysis. *Kluwer Academic Publishers*, Boston, Dordrecht/London, P, 134 – 249, 1998.

ÇOBANOĞLU, F. Measuring the Technical Efficiency of Cotton Farms in Turkey Using Stochastic Frontier and Data Envelopment Analysis. *Outlook On Agriculture*, v. 42, n. 2, p. 125–131, 2013.

FARRELL, M. The measurement of productive efficiency. *Journal of the Royal Statistical Society*, v. 120, n. 3, p. 253-281, 1957.

FATIMA, H.; KHAN, M.A.; ZAID-ULLAH, M.; JABBAR, A.; SADDOZAI, K.N. Technical efficiency of cotton production in Pakistan: A comparative study on non BT and BT-cotton farms. *Sarhad Journal of Agriculture*, v. 32, n. 4, p. 267-274, 2016.

GHEE-THEAN, L.; ISMAIL, M.M.; HARRON, M. Measuring Technical Efficiency of Malaysian Paddy Farming: An Application of Stochastic Production Frontier Approach. *Journal of Applied Sciences*, v. 12, p. 1602-1607, 2012.

GÜL, M.; DAĞISTAN, E.; AKPINAR, M.G.; PARLAKAY, O. Determination of technical efficiency in cotton growing farms in Turkey A case study of Cukurova region. *African Journal of Agricultural Research*, v. 4, p. 944-949. 2009.

HASSAN, S.; AHMAD, B. Technical efficiency of wheat farmers in mixed farming system of the Punjab, Pakistan. *International Journal of Agriculture & Biology, v.* 7, n. 3, p. 431-435, 2005.

HOSSAIN, M.M.; ALAM, M.A.; UDDIN, M.K. Application of Stochastic Frontier Production Function on Small Banana Growers of Kushtia District in Bangladesh. *Journal of Statistics Applications & Probability*, v. 4, n. 2, p. 337-342, 2015.

ISLAM, G.M.; TAI, S.Y.; KUSAIRI, M.N. A stochastic frontier analysis of technical efficiency of fish cage culture in Peninsular Malaysia. *Springerplus*. 2016 July, 19, v. 5, n. 1, p. 1127, 2016.

KARIMOV, A.A. Factors affecting efficiency of cotton producers in rural Khorezm, Uzbekistan: Re-examining the role of knowledge indicators in technical efficiency improvement. *Agricultural and Food Economics*, v. 2, p. 1-16, 2014.

KHAN, D.; ULLAH, A. Comparative analysis of the technical and environmental efficiency of the agricultural sector: The case of Southeast Asia countries, Custos e @gronegócio on line - v. 16, n. 3, Jul/Sep., 2020. (www.custoseagronegocioonline.com.br).

KODDE, D.A.; PALM, F.C. Wald criteria for jointly testing equality and inequality restrictions. *Econometrica*, v. 54, p 1243–1248, 1986.

KUMAR, S.; JAIN, R.; KUMAR, N.R.; BALAJI, S.J.; JHAJHRIA, A.; TATIPUDI, S.V.B.; AWAIS, M. Measuring efficiency of cotton production in Haryana: Applicationof data envelopment analysis, *J. Cotton Res. Dev.* v.33, n. 2, p. 314-323, 2019.

MADAU, F.A. Parametric Estimation of Technical and Scale Efficiency in the Italian Citrus Farming. *Agricultural Economics Review*, v. 12, p. 91-111, 2011.

MAILENA, L.; SHAMSUDIN, M.N.; RADAM, A.; MOHAMED, Z. Efficiency of Rice Farms and its Determinants: Application of Stochastic Frontier Analysis. *Trends in Applied Sciences Research*, v. 9, p. 360-371, 2014.

MANGO, N.; MAKATE, C.; HANYANI-MLAMBO, B.; SIZIBA, S.; LUNDY, M. A stochastic frontier analysis of technical efficiency in smallholder maize production in Zimbabwe: The post-fast-track land reform outlook, *Cogent Economics & Finance*, v. 3, n. 1, 1117189, 2015.

MEEUSEN, W.; VAN DEN BROECK, J. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*. V. 18, p. 435-444, 1977.

MINISTRY OF AGRICULTURE AND FORESTRY (MAF), Cotton in the World. Bulletin of Ministry of Agriculture and Forestry. https://www.tarimorman.gov.tr /BUGEM/Belgeler/M%C4%B0LL%C4%B0%20TARIM/PAMUK%20ARALIK%20B%C3 %9CLTEN%C4%B0.pdf (accessed on 14 July 2020). 2020.

OLATIDOYE, M.S.; ALIMI, T.; AKINOLA, A.A. Quality assessment of the physico-chemical properties of vermiwash produced from different sources during successive storage periods. *Asian J. Agriculture*, v. , n. 2, p. 58-63, 2018.

SHARMA, K.R.; LEUNG, P. Technical Efficiency of the Longline Fishery in Hawaii: An Application of a Stochastic Production Frontier. *Marine Resource Economics*, v. 13, n. 4, p. 259-274, 1998.

SOLAKOGLU, E.G.; ER, S.; SOLAKOGLU, M.N. Technical Efficiency in Cotton Production: The Role of Premium Payments in Turkey. *Transit Stud Rev* v. 20**,** p. 285–294, 2013.

TASILA KONJA, D.; MABE, F.N.; ALHASSAN, H. Technical and resource-use-efficiency among smallholder rice farmers in Northern Ghana. *Cogent Food & Agriculture*, v. 5, n. 1, 1651473, 2019.

TENAYE, A. Technical Efficiency of Smallholder Agriculture in Developing Countries: The Case of Ethiopia. *Economies*, v. 8, n. 2, p. 34, 2020.

THERIAULT, V. The Role of Institutional Environments on Technical Efficiency: A Comparative Stochastic Frontier Analysis of Cotton Farmers in Benin, Burkina Faso, and

Mali. Agricultural and Applied Economics Association (AAEA) Conference Paper,(http://purl.umn.edu/103436), 2011.

TİPİ, T.; YILDIZ, N.; NARGELEÇEKENLER, M.; ÇETİN, B. Measuring the technical efficiency and determinants of efficiency of rice (Oryza sativa) farms in Marmara region, Turkey. *New Zealand Journal of Crop and Horticultural Science,* v. 37, p. 121–29, 2009.

UMAR, H.S.; GIREI, A.A.; YAKUBU, D. Comparison of Cobb-Douglas and Translog frontier models in the analysis of technical efficiency in dry-season tomato production, *Agrosearch*, n. 2, p. 67– 77, 2017.

WADUD, A.; WHITE, B. Farm household efficiency in Bangladesh: A comparison of stochastic frontier and DEA methods. *Applied Economics,* v. 32, p. 1665–1673, 2000.