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FACTORS AFFECTING TECHNICAL EFFICIENCY SCORES ESTIMATED FOR THE COTTON SECTOR OF THE HARRAN PLAIN IN TURKIYE: A STOCHASTIC FRONTIER ANALYSIS

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ABSTRACT

The current study deals with the technical efficiency of cotton farmers operating on the Harran Plain of Turkiye with an application to the two well-known stochastic approaches, i.e., the Cobb-Douglas and the translog stochastic frontier production functions. Using farm-level cross-sectional data, a specialized maximum likelihood technique incorporates both stochastic frontiers and inefficiency effects models into a single equation model to estimate these efficiency scores along with their determinants simultaneously. Calculations indicate that technical inefficiency effects were present in these models. The data used in this research proved to be the best fit for the translog production function in comparison to the specification of the corresponding Cobb-Douglas frontier model. Although partial influences of some of the variables included in the inefficiency effects model were found to be insignificant, all these variables jointly had significant impacts in shaping the inefficiency of the sampled farmers. Results show that factors such as farm experience, education, land fragmentation, off-farm job availability, irrigation frequency, and farm location influence the technical inefficiency effects.

I. INTRODUCTION

There are interesting concerns both in terms of poverty reduction and national economic aspects arising from the role of cotton production in national development in Turkiye. Cotton farming has traditionally been considered the main livelihood of the farm households operating in the major plains of Turkiye. The cotton sector on the Harran Plain, one of the largest plains of the Southeastern Anatolia region in Turkiye, is almost entirely characterized by middle-income cotton producers who were responsible for about 21 percent of the national cotton production. With cotton the most-planted field crop on the Harran Plain, it is commonly accepted among local farmers that cotton is the most profitable agricultural commodity. Between 1995 and 2019, the area under cotton cultivation in Turkiye increased more than twenty times and reached 477,868 hectares with a production amount reaching 2.2 million metric tons [1].

The cotton sector, loaded with a lot of roles in farmers' livelihoods as such, has been disrupted by several problems. First of all, inefficient production techniques lead to low levels of yield and quality factors. Based on a dataset compiled using information gathered from a sample of cotton farmers operating in the Harran Plain, Binici et al. (2006a) reported that most cotton farmers in the region are inefficient input users. In addition, excessive irrigation practices, which are widely applied in the Harran Plain, are the main drivers of increased soil salinity. This problem is due to the shallow groundwater table and can seriously disrupt cotton production [2]–[4].

In addition, the prevailing marketing system in the area is not sufficient to provide local cotton farmers with the possibility of supplying their products at reasonable prices. Factors like these have reducing effects on farmer incomes. As a result, poverty will continue to be a trap for most households. Therefore, improving production performance while ensuring sustainable use of resources is the main challenge for the growth of middle-income cotton farmers. However, the opportunity to improve farm production based on the expansion of cultivated land is limited to meeting the growing demand for cotton required for Turkiye's ever-increasing population. Therefore, advances in technology and productivity/efficiency are the only hope of production increase to meet the increasing demand for cotton.

While production functions of farmers operating at full efficiency level were assumed to be known, it was necessary to estimate these functions based on data using either parametric or non-parametric (also known as Stochastic Frontier Analysis and Data Envelopment Analysis, respectively) techniques as the parameters of such functions always remained unknown in practice. Starting from this point, literature on efficiency has evolved in two directions of which is to use parametric techniques [5]–[17] and the other one is to use non-parametric techniques [18], [19].

The bulk of the literature focusing on parametric techniques has developed in the area where technical efficiency and inefficiency factors are incorporated simultaneously within a stochastic model [7], [9], [15]–[17], [20]–[26]. However, in some empirical papers by opponents of the above method, a two-step procedure was adopted, i.e. stochastic frontier production function parameters were estimated first, and then the estimated technical inefficiency effects were retracted on the various farmer-specific variables that are expected to be important in explaining the level of technical incompetence of the farmers sampled. This two-step approach contradicts standard assumptions that inefficiency effects are independently and identically distributed to estimate unknown values. However, using predicted technical inefficiency effects in a regression model that includes other explanatory variables is not consistent with the assumption of uniformly distributed technical inefficiency effects in the stochastic model [27]. Despite this debate over whether or not either analysis of the impacts of farm-specific factors on productive efficiency should be handled within a simultaneous model, the two-step procedure is still quite popular in determining the linkage between productive efficiency and firm-specific factors.

In Turkish agriculture, it is important to measure efficiency and productivity for several reasons. Firstly, efficiency and productivity are the key indicators to evaluate farm households as they are the accepted performance measures and success parameters. Secondly, to hypothesize the determinants of inefficiency it is important to isolate the impacts of efficiency and productivity from the environmental impacts once they are estimated. Improving the performance of farm households is then closely related to policies that are formed by identifying sources of inefficiency.

II. MATERIALS AND METHODS

II.1 DATA COLLECTED AND THE MATERIAL USED

The research project was started by the University of Harran and funded by the Scientific and Technological Research Council of Turkiye (TUBITAK) with reference number 110K374. Individual units and a subset of survey data were used in this analysis.

The information acquired using a data collecting method also known as the farmer registration information and financial incentive systems, applied to a random sample of cotton farmers working on the Harran Plain, constitutes the majority of the core materials utilized in this article. This method addresses the problem of survey respondents having trouble recalling their responses to questions about their agricultural practices. Farmers are frequently confronted with queries about their previous farming techniques. The study reported in this paper uses farmer diaries based on payments to motivate farmers to voluntarily participate in the survey and so limit the problems generated by the problem of misremembering the answers to comprehensive survey questions.

The implementation of a financial inducement system that allows for the financial and production record keeping with the least amount of information loss would ensure that participant farmers are provided an incentive to complete farmer diaries on a daily or at least weekly basis. As a result, a payment schedule was established, allowing our member farmers to get a one-time-only payment after finishing the diaries after the season.

We used a stratified random sample technique to choose several representative cotton farmers who would be given diaries to fill out beginning with the 2012 crop season. We then administered frequent visits (10 to 20 depending on the location) to these farmers throughout the season to control these diaries. Two steps were taken to carry out the sampling. First, we purposely identified 51 villages based on their representative properties. On the Harran Plain, 1,029 registered cotton farmers were actively farming the crop and these farmers are to be counted as the overall farmer population. In the second stage, a stratified random selection strategy with a 5% acceptable error margin was used to choose a total of 126 cotton farmers to furnish the farmer diaries. This procedure yields four size strata that represent the region's entire farmer population. There will be 49, 49, 21, and 7 cotton growers sampled in each of the four size strata, respectively.

II.2 ANALYTICAL FRAMEWORK

To estimate frontier production functions for efficiency assessments, stochastic frontier analysis (SFA) has been utilized extensively in the literature. The stochastic frontier analysis pays particular attention to how the composite error term takes the form, differentiating between measurement errors and other sources of statistical noise. This is in contrast to Data Envelopment Analysis (DEA), which makes no assumptions about the distributional form for inefficiency terms or the functional forms of production functions. Contrary to what DEA claims, not all deviations from the maximum production are considered to be the result of technological inefficiency from the SFA perspective. With Farrell (1957) [28] reporting that production functions of firms must be estimated using data on individual levels and functional forms, stochastic frontiers have since been developed further capitalizing on this notion [29].

The two major representations of the stochastic frontiers are the Cobb-Douglas model and the Transcendental logarithmic (hereafter, translog) model [30], [31]. The Cobb-Douglas stochastic frontier model imposes several technological constraints, such as requiring constant elasticity of scale and unity elasticity of input substitution. However, the translog stochastic frontier model, which has a flexible functional form, does not impose any such limitations, and the range of the elasticity of substitution ranges from negative infinity to positive infinity. Hence the Cobb-Douglas model is nested in the Translog model.

We can specify these models as:

Cobb-Douglas:

$$lnY_i = \beta_0 + \sum_{i=1}^{6} \beta_i lnX_i + \varepsilon_i \quad (1)$$

Translog

$$lnY_i = \beta_0 + \sum_{j=1}^{6} \beta_j lnX_{ji} + \sum_{j=1}^{6}\sum_{k=1}^{6} \beta_{jk} lnX_{ji}\, lnX_{ki} + \varepsilon_i \quad (2)$$

where Y_i is the i-th firm's output, X_i is a $K \times 1$ vector holding the input logarithms; β is a vector of unknown parameters; and ε_i is the composite error term, which is made up of two distinct error components from different sources, i.e., $\varepsilon_i = v_i - u_i$ where v_is are the error component resulting from measurement errors and other factors beyond the farmer's control and are assumed to follow a normal distribution $N(0, \sigma_v^2)$. The u_is, on the other hand, are non-negative random variables linked to technological inefficiency and are supposed to come from a normal distribution with mean μ and variance σ_u^2, which is truncated at zero from below, where μ is defined as

$$\mu_i = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \delta_5 Z_{5i} + \delta_6 Z_{6i} + \delta_7 Z_{7i} + \delta_8 Z_{8i} + \delta_9 Z_{9i} + \delta_{10} Z_{10i} \quad (3)$$

and where Z_{is} are farm and farmer-specific variables that are hypothesized to have an impact on technical inefficiency level.

Following the γ parameterization of Battese & Cora [6];

$$\gamma = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2} \quad (4)$$

The log-likelihood function for normal and truncated normal pairs may then be written as

$$\ln L = \sum_{i=1}^{N} \left\{ -0.5\ln(2\pi) - \ln\sigma_s - \ln\Phi\left(\frac{\mu_i}{\sigma_s\sqrt{\gamma}}\right) + \ln\Phi\left[\frac{(1-\gamma)\mu_i - \gamma\varepsilon_i}{\{\sigma_s^2\gamma(1-\gamma)\}^{1/2}}\right] - 0.5\left(\frac{\varepsilon_i + \mu_i}{\sigma_s}\right)^2 \right\} \quad (5)$$

Where μ_i is specified as before, $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$, $\Phi(.)$ represents the cumulative distribution function of a standardized normal variable, and ε_i is the composite error term for each firm in question. The parameters, β, σ_s^2, and γ in the above likelihood function are the choice variables for which the values are to be estimated by maximizing the function using the FRONTIER 4.1 computer program developed by Coelli in 1996 [32]. The ratio of the observed output to matching stochastic frontier output is the technical efficiency term for a single data point in SFA:

$$TE_i = \frac{Y_i}{e^{X_i\beta}} = \frac{e^{X_i\beta - u_i}}{e^{X_i\beta}} = e^{-u_i} \quad (6)$$

However, the inefficiency term, u_i is not observed while the composite error term is. Thus estimating technical efficiency scores requires taking the expected value of u_i conditional on $\varepsilon_i = v_i - u_i$ [13]:

$$TE_i = e^{-u_i} = E[e^{-u_i} | \varepsilon_i = v_i - u_i] = \frac{1 - \Phi(\sigma_\Lambda + \gamma\varepsilon_i/\sigma_\Lambda)}{1 - \Phi(\gamma\varepsilon_i/\sigma_\Lambda)} e^{(\gamma\varepsilon_i + \sigma_\Lambda^2/2)} \quad (7)$$

where $\sigma_\Lambda = \sqrt{\gamma(1-\gamma)\sigma_S^2}$; $\varepsilon_i = \ln(Y_i) - X_i\beta$, and the cumulative distribution function of a standardized normal variable is again represented by $\Phi(.)$.

II.3 VARIABLES USED IN THE ANALYSIS

Participants in the survey were also interviewed to answer questions in two categories: (1) production characteristics, which included measures such as the size of operation, type of ownership, commodity yields, and land characteristics; and (2) farmer characteristics, which included gender, age, and education, among others. Table 1 describes the output and input variables that are used to estimate frontier production functions, while Table 2 summarizes the description of the dependent and explanatory (Z) variables that are used in our econometric analysis. These tables per se are self-explanatory and describe the variables used in the analyses quite comprehensively.

Table 1: Definition of the variables used to estimate frontier production functions.

Variables	Definition
Output Variable	
OUTPUT	Quantity of cotton produced in total (kilograms)
Input Variables	
SEED (X_1)	Quantity of seeds used in cotton production (kilograms)
FERTILIZER (X_2)	The variable denoted as FERTILIZER represents the net total amount of ammonium and phosphate contained in commercial brand fertilizers used in cotton production and is measured in kilograms.
LABOR (X_3)	Working hours depleted (family as well as hired labor).
PESTICIDE (X_4)	Value of herbicidal and insecticidal chemicals (TL[1]).
CAPITAL (X_5)	Capital input includes the annualized flow of capital services required by cotton production and is measured in TL.
LAND (X_6)	Land area input is considered as the land area under cotton cultivation and measured in hectares.
[1] Abbreviated for Turkish Liras	

Source: Authors, (2023).

Table 2: Z variables' definition for the stochastic frontier analysis (inefficiency determinants).

Variable	Definition
Dependent Variable	
TE_{VRS}	Technical efficiency is calculated using the assumption of variable returns to scale, with a value ranging from 0 to 1.
Explanatory Variables	
EXPERIENCE (Z_1)	Farmer experience (Years)
EDUCATION (Z_2)	If the farmer attended high school or high school and college, the dummy variable will have a value of 1, otherwise, it will have a value of 0.
HSIZE (Z_3)	Household size; the number of people living in the household.
OFF-FARM (Z_4)	The value of the dummy variable is 1 if the farmer works outside the farm and 0 otherwise.
FMLYLBOR (Z_5)	Share of the family labor force in total labor input (%)
LSEGMENT (Z_6)	Parcel segmentation on land is the number of parcels under the farmer's ownership or tenancy.
LNDOWNR (Z_7)	If the farmer owns the land he farms, the dummy variable will have a value of 1; otherwise, it will have a value of 0.
LOCNHRRN (Z_8)	Dummy variable that indicates the location of the agricultural activity has a value of 1 if it is situated in Sanliurfa's Harran district.
LOCNACKL (Z_9)	Dummy variable that indicates the location of the agricultural activity and returns 1 if the land is in Sanliurfa's Akcakale district.
IRRGFREQ (Z_{10})	Frequency of irrigation applied to the land under cultivation.

Source: Authors, (2023).

Table 3 shows descriptive statistics for the input variables used to estimate production frontiers, whereas Table 4 shows descriptive statistics for farm and farmer characteristics (Z variables) utilized as explanatory factors for examining the drivers of technical efficiency scores.

The variable designated "OUTPUT" is the quantity of cotton produced in total kilograms. Six inputs capturing all the production factors that are used in cotton production (SEED, FERTILIZER, LABOR, PESTICIDE, CAPITAL, and LAND) are considered. Some of these input variables are measured in mass units (i.e., kilograms), while others are expressed in Turkish Liras (TL). The labor input (LABOR) is measured in working hours depleted by the farmer and considers paid and unpaid labor. The variable denoted as CAPITAL quantifies the annualized flow of capital services required by cotton production and is estimated by summing up all the expenses on fixed and variable inputs other than seed, fertilizer, labor, and pesticides. These expenses typically include yearly depreciation, rental costs for the land and/or machinery used in production plus other expenses on fuels and repair and maintenance services for the farm machinery. The variable designated "FERTILIZER" is the net amount of nitrogen plus phosphorus contained in commercial fertilizers applied and measured in kilograms. The variable "SEED" represents the amount of cotton seeds used to sow the field and is measured in kilograms as well. The variable designated "PESTICIDE" consists of such variable expenditures including those for both herbicidal and insecticidal chemicals and is measured in TL.

Using Coelli's FRONTIER 4.1 software developed in 1996 and SFA methodologies separately applied to each frontier production function under the assumptions of variable returns to scale, technical efficiency ratings utilized as the dependent variable in our econometric studies are estimated [32].

Table 3: The input variables' descriptive statistics for estimating stochastic frontiers.

Variables	Mean	Std. Dev.	Minimum	Maximum
Y: Amount of cotton produced (kg)	47,642.619	45,253.108	3,209.000	290,000.000
X_1: Seeds (kg)	306.024	489.567	10.000	4,500.000
X_2: Fertilizer (ammonium+phosphate; kg)	2,925.405	3,081.784	2,200.000	16,740.000
X_3: Labor (Family + hired; hours)	3,944.772	4,217.881	175.300	20,499.000
X_4: Values of Pesticides used (TL)	2,881.470	3,905.217	50.000	31,320.000
X_5: Fixed and variable capital (TL)	31,473.694	35,152.091	933.000	261,271.438
X_6: Land area (ha)	10.790	11.140	0.650	80.000

Source: Authors, (2023).

Table 4: Explanatory variables' descriptive statistics used to assess the inefficiency effects model.

ExplanatoryVariables	Mean	Std. Dev.	Minimum	Maximum	Obs
EXPERIENCE (Z_1)	17.3016	10.1155	2.0	45.0	126
EDUCATION (Z_2)	0.3730	0.4855	0.0	1.0	126
HSIZE (Z_3)	9.8968	7.4176	2.0	55.0	126
OFF-FARM (Z_4)	0.3016	0.4608	0.0	1.0	126
FMLYLBOR (Z_5)	0.3167	0.3135	0.0	1.0	126
LSEGMENT (Z_6)	1.9762	1.3234	1.0	7.0	126
LNDOWNR (Z_7)	0.8254	0.3811	0.0	1.0	126
LOCNHRRN (Z_8)	0.2698	0.4456	0.0	1.0	126
LOCNACKL (Z_9)	0.2381	0.4276	0.0	1.0	126
IRRGFREQ (Z_{10})	**6.6746**	**1.5688**	**3.0**	**12.0**	**126**

Source: Authors, (2023).

Some of the farm and farmer characteristics anticipated to influence technical efficiency scores include single dummy variables quantifying off-farm work status (OFF-FARM), land ownership status (LNDOWNR), and education level

(EDUCATION), as well as a mutually exclusive multiple dummy variable representing farm location (LOCNCNTR, LOCNHRRN, and LOCNACKL). Other determinants affecting farmer performances are farming experience in years (EXPERIENCE), household size (HSIZE), number of parcels under the farmer's ownership or tenancy (LSEGMENT), and number of irrigation applied (IRRGFREQ). To quantify the effects of the proportion of family labor input in the entire labor force (measured in continuous percentages), we lastly incorporate the variable FMLYLBOR. The location dummies are used to identify the impacts of farmer locality on their performance measures. Due to improved access to knowledge, it is speculated that farmers in the central area are technically more efficient than those working in the Harran and Akcakale districts. Dropping one of the dummy variables from the analysis and using it as a reference variable instead would help avoid dummy trap problems and thus we followed this rule for all the dummy variables in our econometric analysis to keep the consistency throughout. The variable designated LNDOWNR quantifies the effects of land ownership status and could have an ambiguous impact on efficiency. Efficiency might be enhanced by applying soil-improving techniques, an incentive created by land ownership status. However, the tenant farmer may be encouraged to use inputs more effectively by his or her status as a land renter.

A bigger percentage of hired labor may indicate a more specialized, and hence productive, labor input, but it may also be a source of moral hazard. The influence of the amount of family labor might go either way (positive or negative) [33]. Experienced farmers tend to operate more professionally; therefore, it would stand to reason that experience would increase efficiency. However, other writers explore reasons for the reverse connection [34], maybe because farming becomes more physically demanding as the farmer ages (e.g., age impairments-non linearity). Similarly, we hypothetically attach higher efficiency scores to those full-time experienced farmers who are more educated with smaller household sizes, operate on a smaller land tract divided by a smaller number of parcels, and finally irrigate the land more sensibly.

III. RESULTS AND DISCUSSION

In Table 5, the maximum likelihood estimates of the coefficients for the translog stochastic frontier model and the Cobb-Douglas model are shown. All the β coefficients from the Cobb-Douglas frontier model have expected signs and three of these coefficients turn out to be considered significant demonstrating the robustness of the model. In the translog frontier model, nine out of the twenty-seven coefficients are significant at the %1 level, four are significant at the %5 levels, and just one is significant at the %10 levels. Thus the translog frontier model is robust as well.

We check to see if the technical efficiency estimates produced from the two models have different means and variances. Even though the generalized likelihood ratio (LR) test indicates that the translog stochastic frontier model is an appropriate representation, we additionally investigate the sensitivity of technical efficiency levels to the functional form choice. Table 6 shows the production elasticities of individual inputs along with scale parameters. Both models yield production elasticities with all their signs (positive) in the direction expected. The land has the highest production elasticity indicating that it is the most prevalent factor of production. This finding is consistent when we particularly consider how scarce the land is to the farm households in Turkiye. This implies that farm households may be encouraged to continue cultivating their current land parcels.

The factors designated CAPITAL and PESTICIDE appear to be the second and third important factors of production, respectively, for the Cobb-Douglas frontier model while FERTILIZER and SEED inputs for the translog frontier model. These inputs (SEED, PESTICIDE, and FERTILIZER) are land-enforcing factors of production tending to increase the productivity of existing land tracts and thereby promoting yields per hectare. In Turkiye, land degradation brought by elevated soil salinity and wind erosion is the number one constraint on the production and it is possible to state that efficient utilization of fertilizer, seed, and pesticides as well as a suitable combination of the three can mitigate the effects of this constraint. The scale elasticities for the Cobb-Douglas and translog frontier models are 0.96639 and 0.95124, respectively, implying slightly diminishing returns to scale. This means that the farmers are not the best operators in terms of production size.

III.1 EFFECTS OF TECHNICAL INEFFICIENCY

The two key metrics used to assess the overall consequences of technical inefficiency are σ^2 and γ. Both the Cobb-Douglas and the Translog frontier models' predicted values of σ^2 and γ are statistically significant to differing degrees (5% in the Cobb-Douglas model and 1% in the Translog model). This result agrees with previous findings. The Cobb-Douglas and Translog frontier models' estimated values are very substantially different from zero, indicating that the random component of the inefficiency effects considerably affects the level and variability of production for these sampled farmers. This finding is consistent with those found by Wadud (2003) [30], Sharma et al. (1999) [24], and Coelli and Battese (1996) [35]. The Cobb-Douglas and Translog frontier models' respective generalized LR tests, designated as test number 1 in Table 7, lead us to strongly reject the null hypothesis that there is no technological inefficiency at the 5% level. This reveals the randomness of technical inefficiency effects in both models for the farm households operating on the Harran Plain of Turkiye. As a result, their standard response functions are insufficient representations of cotton output.

The generalized LR test presented in Table 7 further illustrates that the stochastic frontier model's explanatory factors, which are unique to the farm setting, have collectively influenced the level of technical inefficiency at the 5 percent level for both frontier models. Given that these factors are likely to have an impact on the productivity of local cotton farmers, it is crucial to look at the signs of the predicted coefficients for δ_i parameters linked to the various explanatory variables in both stochastic frontier models.

In all models, the signs of the estimates for the coefficients of farming experience are positive, showing that experienced farmers are technically less efficient than rookie farmers. While this compares to previous results obtained by several researchers [9], [30], [36], it contradicts the finding obtained by Sesabo and Tol (2007) [25]. This could be attributable to easier credit availability for younger farmers. The coefficients of education in the two models as measured by a dummy variable (taking on values of 1 if the farmer has a high school or college degree) have positive signs indicating that higher education causes inefficiency which is not in the direction expected (significant at 10% and 5% significance levels, respectively). This conforms to the results found elsewhere [24], [35].

Table 5: Estimates of the stochastic frontier models using the maximum likelihood technique.

Variables	Parameters	Cobb-Douglas		Translog	
		Coefficient	**t-ratio**	**Coefficient**	**t-ratio**
Intercept	β_0	6.80800***	13.63900	1.22817	0.93423
Ln X_1	β_1	0.00684	0.09622	4.78501***	4.26456
Ln X_2	β_2	0.02476	1.04251	-2.36477***	-2.82885
Ln X_3	β_3	0.00158	0.07597	-0.31636	-0.54166
Ln X_4	β_4	0.09822***	3.21313	2.55431***	3.23434
Ln X_5	β_5	0.14152**	2.18146	-0.20837	-0.24001
Ln X_6	β_6	0.69347***	7.27066	-3.09795***	-3.18605
Ln X_1 x Ln X_1	β_7	-	-	-0.21986	-1.57440
Ln X_2 x Ln X_2	β_8	-	-	0.00384	0.25583
Ln X_3 x Ln X_3	β_9	-	-	0.08629***	3.22509
Ln X_4 x Ln X_4	β_{10}	-	-	-0.00548	-0.15746
Ln X_5 x Ln X_5	β_{11}	-	-	-0.17555**	-1.97206
Ln X_6 x Ln X_6	β_{12}	-	-	-0.47077**	-2.30417
Ln X_1 x Ln X_2	β_{13}	-	-	0.02238***	0.08841
Ln X_1 x Ln X_3	β_{14}	-	-	-0.21902**	-2.08172
Ln X_1 x Ln X_4	β_{15}	-	-	-0.34772***	-2.98692
Ln X_1 x Ln X_5	β_{16}	-	-	-0.01519	-0.07083
Ln X_1 x Ln X_6	β_{17}	-	-	0.92179***	2.71673
Ln X_2 x Ln X_3	β_{18}	-	-	-0.04185	-0.68130
Ln X_2 x Ln X_4	β_{19}	-	-	-0.18338*	-1.73789
Ln X_2 x Ln X_5	β_{20}	-	-	0.46272***	3.03556
Ln X_2 x Ln X_6	β_{21}	-	-	-0.30251	-1.27172
Ln X_3 x Ln X_4	β_{22}	-	-	-0.07313**	-2.15759
Ln X_3 x Ln X_5	β_{23}	-	-	0.07281	0.94844
Ln X_3 x Ln X_6	β_{24}	-	-	0.13279	0.99296
Ln X_4 x Ln X_5	β_{25}	-	-	0.02049	0.22763
Ln X_4 x Ln X_6	β_{26}	-	-	0.56468***	3.37801
Ln X_5 x Ln X_6	β_{27}	-	-	-0.20888	-0.85362
Inefficiency Model					
Intercept	δ_0	-2.71358	-1.60431	-3.19604**	-2.37611
EXPERIENCE	δ_1	0.02652*	1.70008	0.03161**	2.49135
EDUCATION	δ_2	0.59905*	1.81157	0.86594**	2.37613
HSIZE	δ_3	-0.03301	-1.58264	-0.09435*	-1.99631
OFF-FARM	δ_4	-0.36591	-1.41754	-0.44124**	-2.12623
FMLYLBOR	δ_5	0.92596	1.64717	0.21261	0.89593
LSEGMENT	δ_6	0.17590**	2.22275	0.08836**	2.16400
LNDOWNR	δ_7	-1.31317**	-2.42846	-0.29433	-1.54436
LOCNHRRN	δ_8	1.64662*	1.93193	1.18174***	2.68159
LOCNACKL	δ_9	1.61760**	1.96370	1.12603***	2.70968
IRRGFREQ	δ_{10}	0.06700	1.14677	0.14315**	2.34143
Diagnostics					
Sigma-squared	σ^2	0.25618**	2.41275	0.17952***	3.16563
Gamma	$\gamma=\sigma_u^2/(\sigma_v^2+\sigma_u^2)$	0.91644***	29.04133	0.91630***	23.72817
Sigma V-squared	σ_v^2	0.02141	---	0.01502	---
Sigma U-squared	σ_u^2	0.23477	---	0.16449	---
Log Likelihood	$\ln L(y\|\beta,\sigma,\gamma)$	23.11763	---	42.08589	---

Source: Authors, (2023).

Table 6: Output elasticities of inputs used in cotton production.

Inputs	Cobb-Douglas	Translog Frontier	Inputs	Cobb-Douglas	Translog Frontier
SEED	0.00684	0.07933	PESTICIDE	0.09822	0.05897
FERTILIZER	0.02476	0.09948	CAPITAL	0.14152	0.01843
LABOR	0.00158	0.02593	LAND	0.69347	0.66910
Return to Scale	**0.96639**	**0.95124**			

Source: Authors, (2023).

Table 7: Hypothesis tests for the stochastic frontier and inefficiency effects models.

Null Hypotheses	Log Likelihood	χ^2 Statistic	$\chi^2_{0.95}$ Critical	Decision
Cobb-Douglas Unrestricted Model	23.11763			
1. H$_0$: $\gamma = \delta_0 = \delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	-1.89620	50.02766	22.40	Reject H$_0$
2. H$_0$: $\gamma = \delta_0 = 0$	13.44472	19.34582	5.99	Reject H$_0$
3. H$_0$: $\delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	11.98264	22.26998	18.30	Reject H$_0$
4. H$_0$: $\delta_0 = 0$	20.97651	4.28224	3.84	Reject H$_0$
Translog Unrestricted Model	42.08589			
1. H$_0$: $\gamma = \delta_0 = \delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	17.20815	49.75548	22.40	Reject H$_0$
2. H$_0$: $\gamma = \delta_0 = 0$	35.37227	13.42724	5.99	Reject H$_0$
3. H$_0$: $\delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	30.52162	23.12854	18.30	Reject H$_0$
4. H$_0$: $\delta_0 = 0$	38.51215	7.14748	3.84	Reject H$_0$
Testing Cobb-Douglas Unrestricted Model = Translog	42.08589			
5. H$_0$: $\boldsymbol{\beta_7 = \beta_8 = \beta_9 = \beta_{10} = \ldots = \beta_{27} = 0}$	**23.11763**	**37.93652**	**32.7**	**Reject H$_0$**

Source: Authors, (2023).

The coefficients of the variables designated HSIZE and OFF-FARM are estimated to be negative, implying that household size and off-farm employment availability have a beneficial influence on efficiency, albeit these coefficients are only significant in the translog frontier model. This is not consistent with the findings by Sesabo and Tol (2007) [25]. The estimates for the coefficients of the share of the family labor force in total labor input and the number of irrigation applied to turn out to be positive showing evidence of lowered efficiency levels as they tend to increase. However, the coefficients of the share of family labor input are not significant in both models while the coefficient of irrigation frequency is only significant at the 5% level in the translog stochastic frontier model. Although these findings about family labor input and irrigation frequency satisfy our initial expectations there are no similar results in the literature to which we can compare our findings.

The signs of the estimates for the coefficients of land disintegration as measured by the number of parcels under ownership or tenancy are estimated to be positive which translates into a negative impact on efficiency, i.e., the greater the plot size the lower the efficiency. This finding runs along similar lines to the results obtained by Coelli and Battese (1996) and Wadud (2003) [30], [35]. The estimates for the coefficients of the dummy variable capturing the land ownership status have negative signs indicating that land owners are associated with higher efficiency levels than tenants (only significant in the Cobb-Douglas stochastic frontier model). This is perhaps because landowners would feel more responsible for tracts they operate on resulting in greater engagement of infrastructural investments and that would in turn result in greater efficiency levels. Last but not least, the outcomes of the two models show that the efficiency is negatively impacted by the location dummies for the districts of Harran and Akcakale. This indicates that farmers in the province of Sanliurfa's core area are associated with higher efficiency levels. This conclusion may be explained by the fact that farmers in the central district have easier access to financial instruments such as credits, derivative products, etc.

Results indicate that farm households have technical efficiency scores which substantially differ across the sample. Technical efficiency scores for the Cobb-Douglas frontier model range from 0.30 to 0.98, with a mean of 0.87 and a standard deviation of 0.12, while technical efficiency scores for the translog stochastic frontier model are predicted to range from 0.28 to 0.97, with a mean of 0.88 and a standard deviation of 0.11. The technical efficiency scores' frequency distributions are shown in Table 8 along with their summary statistics. The table shows that it is possible to enhance farm income and thereby welfare by improving efficiency. Production costs could be reduced by 12 percent if full technical efficiency levels were attained by farmer operations.

Table 8: Frequency distribution of farm-specific technical efficiency.

Efficiency Distribution (%)	Cobb-Douglas Stochastic Frontier		Translog Stochastic Frontier	
	Number of Farms	% of Farms	Number of Farms	% of Farms
0-60	3	2.38	5	3.97
60-65	5	3.97	2	1.59
65-70	4	3.17	2	1.59
70-75	3	2.38	1	0.79
75-80	3	2.38	5	3.97
80-85	17	13.49	16	12.70
85-90	26	20.63	17	13.49
90-95	54	42.86	54	42.86
95-100	11	8.73	24	19.05
Mean	86.5		87.9	
Minimum	30.4		28.2	
Maximum	97.5		97.4	
Standard Deviation	**11.5**		**11.2**	

Source: Authors, (2023).

IV. CONCLUSIONS

The Cobb-Douglas and translog stochastic frontier models are used in this study to examine the potential for finding technical inefficiency in terms of its patterns and sources for the case of local cotton growers working on Turkiye's Harran Plain. A specialized maximum likelihood estimation model is applied to estimate these efficiency scores along with their determinants simultaneously with the incorporation of stochastic frontiers and inefficiency effects into a single equation system. The inefficiency effects include such factors, namely education, farm experience, household size, off-farm job availability, the share of the family labor force, land fragmentation, land ownership status, irrigation frequency, and location of the farm relative to the central district of Sanliurfa. The system generates parameters of output elasticities calculated from both the stochastic frontier models, with their signs pointing in the desired directions. The study's findings demonstrate that the sampled local farm households exhibit slightly declining returns to scale in cotton production. The two well-known stochastic models, namely the Cobb-Douglas and the translog frontiers, generate wide ranges of technical efficiency scores that vary from 30% to 98% with a mean of 87% and 28% to 97% with a mean of 88%, respectively. It was detected that full technical efficiency levels attained by farmers ensure a reduction in production cost by 12%.

The findings of the study show that technical efficiency is significantly impacted by farm-specific explanatory factors included in the technical inefficiency effects model. Ironically the older, experienced farm Households with greater education tend to operate farming activities inefficiently. Technically speaking, the farm households operating in Sanliurfa's central region are more productive than those in Akcakale and Harran districts. Moreover, farm households that operate on larger, more fragmented land holdings are inherently less efficient. The well-being of farm households should be improved by robust agricultural policies targeting to reduce land fragmentation and increase technical efficiency and thereby improving farm income.

V. AUTHOR'S CONTRIBUTION

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