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Measuring Technical Efficiency of Wheat Production in Southeastern Anatolia with Parametric and Nonparametric Methods

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Abstract: This study estimates technical efficiencies of wheat growing farmers in Southeastern Anatolia region of Turkey using both parametric and non-parametric methods. The empirical application uses farm level data collected from 75 farms following 2003/2004 growing season. According to the results of the Data Envelopment Analysis (DEA) model, mean efficiencies of wheat growing farmers were estimated to be 0.72 and 0.79 for constant and variable returns to scale (CRS and VRS) assumptions respectively. Predicted technical efficiencies with stochastic frontier model vary widely among farms, ranging between 0.34 and 0.93 and a mean technical efficiency of 0.73. A strong correlation was found between the results obtained with output oriented CRS-DEA and stochastic frontier model. Based on these results, sample wheat producers could increase their output by 21-27% through better use of available resources. Further studies are required in order to determine causes of inefficiencies.

Key words: Technical efficiency, wheat, Turkey, data envelopment analysis, stochastic frontier analysis

INTRODUCTION

Turkey is among major wheat producers in the world. Traditional cereals have an important role in total agricultural production. In particular, wheat and barley are the most important crops among cereals.

Wheat has been grown in Anatolia for thousands of years and is a part of life in rural areas. It is grown on 35.5% of total agricultural land. Approximately 36.1% of the production is for self consumption of the farmers (SIS., 2003).

The principal objectives of the Turkish cereal policy are stabilizing grain prices, meeting nutritional needs of the growing population and developing export potential of Turkish grains and grain products.

As a part of its free market policy, Turkey is replacing traditional support policies with more market oriented ones. For this reason, farmers are expected to operate under much more competitive conditions and increase their efficiencies to survive. Determining existing levels of efficiency will help government searching new policy tools.

Wheat has also a greater importance for the region studied in this paper. Share of wheat within cropping pattern of the region is approximately 40%.

In recent years, DEA has been occasionally been used to analyze agricultural production. Isikli *et al.* (2001) estimated technical efficiencies of tobacco production in Turkey, calculated input losses and explained their implications for Turkish economy. Abay *et al.* (2004) applied DEA analysis using data obtained from 300 farms and found a strong positive relationship between input use efficiency in tobacco farming and sustainability of agriculture.

Alemdar and Ören (2006) identified determinants of technical inefficiency in wheat growing farms in Southeastern Anatolia with DEA analysis. In this study, the researchers used farm level data obtained from 193 farms following 2000-2001 growing season.

The purpose of this study is to investigate technical efficiency of wheat farms in Southeastern Anatolia Region. For this reason both parametric and non-parametric methods were used. It is important to underline that the objective of using two different approaches is not comparing the methods but obtaining more reliable efficiency estimates since each method has its own kind of weaknesses and strengths.

MATERIALS AND METHODS

Study area and data collection: Southeastern Anatolia region is among the less developed regions of Turkey. Per capita income in this region is approximately half of the average per capita income in Turkey (DPT, 2004). This is

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also a region where a great imbalance exists in land ownership distribution. Population growth rate is high, educational level of the farmers is very low. Due to high population growth, average farm family consists of 9.8 persons (twice as much as country average). Agriculture depends on crop production. Major crops grown in the area are wheat, barley, cotton and lentils. Low income and high population causes migration to the cities and other regions.

Following 2003/2004 production period, a questionnaire study was conducted and 132 farms growing several traditional crops (wheat, barley, lentils and cotton) were selected with a stratified random sampling procedure. The survey covered three provinces (Şanlıurfa, Diyarbakır and Mardin) with great agricultural potential in Southeastern Anatolia Project.

For this study, only data related to wheat growing farms were used in efficiency analysis. Number of wheat growing farms is seventy-five. These farms are operating under similar climatic, social and economic conditions. All the sample farms grow wheat on similar types of soils.

Analytical procedures for measuring technical efficiency: Measurement of efficiency and estimation of production frontiers were developed explosively after Farrell's (1957) seminal work providing definitions and a computational framework for technical and allocative efficiency. DEA and SFA are the two most important alternative approaches in this respect.

Both methods construct a production frontier and compares efficiency of production units with respect to this frontier. Constructed production frontier defines the maximum output possible from a given input combination for a given technology. In parametric models (SFA), parameters of production functions are determined statistically. In non-parametric approach (DEA), a piecewise linear function is constructed from observed data and no functional form is assumed.

In DEA, there is no need to impose any explicit functional form for the underlying technology and this approach can easily accommodate multiple outputs. These are main strengths of DEA approach. However, DEA is a deterministic method and it attributes all deviations from the piece-wise linear frontier to inefficiencies. A frontier estimated by DEA is very sensitive to measurement errors and other noise in data.

Stochastic noise is taken into account in SFA. However, assuming a priori distributional forms for inefficiency component and imposing an explicit functional form for the underlying technology are the major weaknesses of SFA approach.

In agricultural economics literature, use of stochastic frontier methods is recommended because of the inherent nature of uncertainty associated with agricultural production (Coelli *et al.*, 1998). Production uncertainties may arise due to bad weather conditions, pests, diseases and other factors. However, since each technique has different strengths and weaknesses, some researchers use both methods for the same data set and compare the results obtained (Sharma *et al.*, 1997, 1999; Chakraborty *et al.*, 2002; Iráizoz *et al.*, 2003; Kwon and Lee, 2004). This approach is adopted in this study.

Data analysis: DEA is a nonparametric method of estimating relative efficiencies of decision making units with multiple inputs and/or multiple outputs. Two most widely used DEA models are CCR (Charnes and Cooper, 1978) and BCC (Banker *et al.*, 1984) models. While CCR model assumes constant returns to scale, BCC model allows for variable return to scale conditions.

An output oriented BCC model can be written as a series of N linear programming problems, one for each decision making unit producing M outputs using K different inputs:

$$\text{Max}_{\varphi,\lambda} \quad \varphi$$

subject to

$$\begin{aligned} -\varphi y_i + Y\lambda &\geq 0 \\ x_i - X\lambda &\geq 0 \\ \lambda &\geq 0 \\ N1'\lambda &= 1 \end{aligned}$$

where, $1 \leq \varphi < \infty$ and φ-1 is the proportional increase in outputs that could be achieved by the i-th DMU, with input quantities held constant. Y is (M x N) output matrix, X is (K x N) input matrix, y_i is the output of i-th firm, N1′ is a vector of (N x 1) and a convexity restriction, λ is (Nx1) vector of intensity variables. $1/\varphi$ defines a technical efficiency score between zero and one.

Original specification has been extended in several ways and multi stage models were developed in order to meet more strict Koopmans (1951) criteria, to identify the nearest efficient points and to make the model invariant to units of measurements. Coelli (1996b, 1997) developed such a multi stage methodology and a computer program (DEAP) which implements a robust multi-stage model among other options.

A ratio of technical efficiency scores obtained from DEA under CRS and VRS assumptions measures scale efficiency. A value of scale efficiency equal to one implies that the farm is scale efficient and a value less than one suggests the farm is scale inefficient. A farm is scale inefficient when it produces inefficiently large output under decreasing returns to scale (super-optimal) conditions or produces inefficiently small output under increasing returns to scale (sub-optimal) conditions.

A critical issue in non-parametric programming technique is the selection of inputs. As some researchers observed, estimated results are sensitive to the number of inputs included to the programming model. (Seiford and Thrall, 1990; Tauer and Hanchar, 1995). Number of observations should exceed total number of inputs and outputs several times. According to Fernandez-Cornejo (1994) a dimensionality ratio (K/N+M) larger than five will differentiate the efficiency among farmers. In this ratio K, N and M represents number of observations, inputs and outputs respectively. Cooper *et al*. (2000) give a rough rule of thumb as follows:

$$n \geq \max \{m \times s, 3\,(m + s)\}$$

where n = number of DMUs, m = number of inputs and s = number of outputs.

Suggested dimensionality ratio and rule of thumb were taken into consideration and the following parameters were selected to be included into the models:

One output and six inputs were used in the models. The only output is the wheat yield per unit area (kg ha^{-1}). Inputs include seed, fertilizer-N, fertilizer-P, labor, machinery operating time and pesticide costs (1000 TL da^{-1}). Expenses on these inputs consist 94.74% of all variable costs.

Seed is expressed as the amount used in production (kg ha^{-1}). It is produced by the farmers themselves. Fertilizer-N and fertilizer-P parameters represent pure nitrogen (kg-N ha^{-1}) and pure phosphorus applied (kg P_2O_5 da^{-1}). Labor (h ha^{-1}) represents total amount of family and hired labor used in wheat production from land preparation through harvest. Farm machinery operating time (h ha^{-1}) represents tractor hours used in production from land preparation through harvest. Pesticide cost (1000 TL da^{-1}) is the only non-physical parameter in the model and represents total costs of herbicides, insecticides and seed treatment chemicals. Some descriptive statistics on input and output parameters are presented in Table 1.

As it is seen from Table 1, large variations exist in some of the inputs. The greatest variation is in pesticide cost and labor use, respectively. Such a great variation in input use levels may be an indication of a mismanagement problem.

An output oriented DEA model was chosen in order to make results more comparable with those obtained from stochastic frontier. Both techniques consider the observed production relative to the corresponding production potential, given the quantities of inputs used.

Table 1: Summary statistics for variables used in the efficiency analysis

Input/Output variables	Min.	Max.	Mean	SD*
Output :				
Wheat yield (kg ha^{-1})	700	4700	2388	937
Inputs :				
Seed (kg ha^{-1})	91.38	346.37	227.70	54.59
Fertilizer-N (kg N ha^{-1})	12.25	207.12	85.52	36.77
Fertilizer-P (kg P_2O_5 ha^{-1})	16.00	137.54	61.05	26.80
Labor (h ha^{-1})	0.95	51.50	12.60	13.54
Machinery (h ha^{-1})	2.30	41.71	9.50	7.30
Pesticide (1000 TL ha^{-1})	1941	125820	23726	24121

* Standard deviation

Using DEAP software developed by Coelli (1996b), a multi-stage DEA model was employed and efficiency scores were estimated under both CRS and VRS assumptions.

Stochastic frontier analysis: Stochastic frontier model was introduced by Aigner *et al*. (1977) and Meeusen and van den Broeck (1977). A stochastic frontier model for a firm (i), producing Y output using X inputs are given below:

$$Y_i = X_i\,\beta + V_i - U_i \tag{1}$$

In Eq. (1) random error (Vi) accounts for measurement error and other random factors and combined effect of other unspecified input variables in the production function. Vi component can either be positive or negative. On the other hand, technical efficiency component (U_i) must be positive.

The ratio of the observed output of the i-th firm, relative to the potential output estimated by Eq. (1) gives the technical efficiency of i-th firm. Hence technical efficiency denoted by TE_i is given by:

$$TE_i = \exp(-u_i) \tag{2}$$

Battese and Corra (1977) suggested a gamma ($\gamma = \sigma^2/\sigma_s^2$) parameter, which can take a value between zero and one. A value of γ = 0 indicates that the deviations from the frontier are due entirely to noise, while a value of one would indicate that all deviations are due to technical inefficiency.

SFA scores and coefficients of the production function were estimated using FRONTIER software developed by Coelli (1996a). A Cobb-Douglas production function was assumed for simplicity and convenience. A translog function and other generalized functions were not used because of potential multicollinearity problems and loss of degrees of freedom.

RESULTS AND DISCUSSION

Efficiency scores: Out of the 75 wheat farms studied, 21 farms under CRS and 28 farms under VRS are fully efficient. 5 farms under CRS and 2 farms under VRS showed a performance below 0.40. On the other hand no farm was found to be fully efficient with SFA. The greatest efficiency score was found to be 0.93 (Table 2).

The signs of the all coefficients except fertilizer-N are positive. Except pesticide, all coefficients are found to be statistically significant. Negative sign of Fertilizer-N parameter implies an excessive use of this input. Thus, level of fertilizer-N could be reduced without a reduction in output levels (Table 3).

The test statistics for the general likelihood test for $\gamma = 0$ had a value of 4.128. The null hypothesis that there is no technical inefficiency in the model is rejected at the 5% level, indicating the coefficients of the frontier production function are significantly different from the average production function estimate by OLS (Battese and Coelli, 1988; Coelli, 1996a).

Efficiency scores given to each individual farm and mean efficiencies were different between different models. This is expected to a certain extend since different models work under different assumptions.

Since DEA attributes any deviation from the frontier to inefficiencies, DEA efficiency scores are expected to be less than those obtained with SFA. However this is not the case in this study. SFA gave lower scores than DEA. When DEA frontier tightly envelopes data this may occur. Sharma *et al.* (1997) reports such a situation in their study where they investigated productive efficiency of the swine industry in Hawai and compared results from parametric and non-parametric methods.

The differences in efficiency scores between DEA and SFA may also be explained as follows: farms appearing less efficient under SFA have a relatively large inefficiency component (u) of the error term compared to the random component (v).

Spearman correlation coefficients between the technical efficiency scores were computed and given in Table 4 in order to examine agreement between results obtained from DEA and SFA. All correlation coefficients are positive and significant at 0.01 level. This indicates a strong agreement between results. The strongest correlation is between stochastic frontier and DEA, CRS models.

A further analysis was carried out in order to see whether both approaches identify the same farms as "best-practice" and "worst-practice". For this purpose, farms were sorted according to their DEA and SFA efficiency scores. Top and bottom quarters of those lists were compared. 67% of the farms identified by SFA as "top 18 best-practice farm list" also appeared in the "top 18 best-practice farm list" of CRS DEA. The same analysis was applied for the bottom quarter (worst-practice). Seventy eight percent of the farms having been identified by one method as having efficiency scores in the bottom quarter also appeared in the bottom quarter identified by the other method. Best and worst case practice correspondences (67 and 78%, respectively) were found statistically different from 25% correspondence which a random chance would yield. As a result of this analysis, different estimates obtained by different methods were found consistent.

As a result it can be confidently stated that efficiencies of the farms studied lie somewhere between 0.73 and 0.79 (Table 5).

In DEA analysis, 3 farms became a peer 20 or more than 20 times for other farms. Those farms were identified as robustly efficient farms since their production practices are such that they were frequently used to construct the

Table 2: Frequency distributions of technical efficiency scores obtained by SFA and DEA models

		DEA		
Efficiency Scores	SFA	CRS	VRS	SE
1.00	-	21	28	21
0.90-1.00	3	1	4	30
0.80-0.90	21	6	6	17
0.70-0.80	27	9	12	3
0.60-0.70	13	16	7	1
0.50-0.60	5	9	11	1
0.40-0.50	2	8	5	1
0<0.40	4	5	2	1
Mean	0.73	0.72	0.79	0.92
Minimum	0.34	0.25	0.25	0.31
Maximum	0.93	1.00	1.00	1.00
Standard deviation	0.14	0.22	0.21	0.13

Table 3: Coefficients of stochastic frontier function

Variables	Coef.	SE	t
Intercept	5.069	0.875	5.790
Ln (Seed)	0.327	0.150	2.176
Ln (Fertilizer-N)	-0.089	0.083	-1.120
Ln (Fertilizer-P)	0.235	0.084	2.790
Ln (Labor)	0.108	0.048	2.236
Ln (Machinery)	0.103	0.088	1.168
Ln (Pesticide)	0.027	0.044	0.602
σ^2	0.243	0.063	3.841
γ	0.824	0.117	7.045
Log-likelihood (H_1)	-25.744		
Log-likelihood (H_0)	-23.680		
Log-likelihood test	4.128		

Coef: Coefficients; S.E.: Standard error; t: t-statistics

Table 4: Spearman correlation coefficients among alternative efficiency measures*

	TE-DEA (CRS)	TE-DEA (VRS)	TE-SFA
TE-DEA (CRS)	1.000		
TE-DEA (VRS)	0.829	1.000	
TE-SFA	0.804	0.596	1.000

*All the correlation coefficients are significant at the 0.01 level (2-tailed)

Table 5: Correspondence (%) of best-practice and worst-practice farms across methods

	DEA-CRS	DEA-VRS	SFA
Best practice farms			
DEA-CRS	-	83.33**	66.67**
DEA-VRS	83.33**	-	50.00**
SFA	66.67**	50.00**	-
Worst practice farms			
DEA-CRS	-	83.33**	77.78**
DEA-VRS	83.33**	-	66.67**
SFA	77.78**	66.67**	-

** Significantly different from 0.25 at 0.01 level

efficient frontier for the other farms. When farms were sorted in descending order according to their SFA efficiency scores, all of these farms appeared within the top quarter (i.e., among best-practice farms).

Study indicates that there are important resource use inefficiencies in wheat production in Southeastern Anatolia Region. Mean efficiency scores vary between 0.72 and 0.79. These results indicate that technical efficiencies can be increased by at least 21% through better use of available resources, given the current state of technology. This can be achieved through improving farmer specific factors, including access to extension services.

Findings also show that it is wise to use different models and methods, compare to results and use researcher's knowledge on the subject before arriving at a definitive conclusion. Such an approach gives a range within which the true efficiency may lie. The narrower the range, the more confident the researcher can be about the results obtained. When the results obtained by different techniques are quite similar, they can be considered more consistent and meaningful.

In this study, both DEA CRS and SFA models gave results supporting each other to a great extent. Average efficiency scores were not found significantly different from each other (0.72 and 0.73, respectively). Both methods identified almost the same units as best practice and worst practice farms. Farms with high peer counts also appeared in SFA top 25% best practice farm list. These facts show that the both methods could be used as complementary tools in order to get more robust results.

Return to scale properties: For the inefficient farms, the causes of inefficiency may be either inappropriate scale or misallocation of resources. Inappropriate scale suggests that the farm is not taking advantage of economies of scale, while misallocation of resources refers to inefficient input combinations. In this study, scale efficiencies are relatively high. Therefore, efficiencies are mainly due to improper input uses.

Mean scale efficiency of the sample wheat farms is 0.92. Of the 75 wheat farms, 22 show constant returns to scale, 24 show increasing returns to scale and 29 show decreasing returns to scale. As it is seen from the Table 6, mean farm size and mean output are 8.05 ha and 3000 kg ha^{-1}, respectively for full efficient farms. The greatest full efficient farm size was found to be 20 ha.

Table 6: Characteristics of farms with respect to returns to scale

	No. of farms	Mean farm size (ha)	Mean output (kg ha^{-1})
Sub-optimal	24	5.80	1572
Optimal	22	8.05	3000
Super-Optimal	29	9.41	2569

Table 7: Input slacks and number of farms using excess inputs

Input	No. of farms	Mean slack	Mean input use	Excess input use (%)
Seed	22	11.66	227.70	5.12
Fertilizer-N	38	15.11	85.53	17.67
Fertilizer-P	18	6.47	61.05	10.60
Labor	26	4.71	12.60	37.38
Machinery	24	2.06	9.50	21.68
Pesticide costs	27	7038	23726	29.66

The scale properties given by SFA analysis can be observed by examining sum of β values presented in Table 3. Sum of coefficients is less than one. This indicates that wheat production in the study area follows the law of decreasing returns to scale.

There is not a strong agreement on input use between different methods. DEA results on slacks show that labor, pesticide and machinery costs could be reduced to a great extent, while remaining at the same production level. Since there are other studies and evidences supporting this, this result seems realistic. When opportunity cost of labor is too low and farmers do not have other opportunities rather than farming, labeling excess labor use (particularly family labor) as inefficient is a subject of debate. Therefore policy should target providing a solution to hidden unemployment, very small farm sizes and also apply a land consolidation program. Creating permanent off-farm employment and income opportunities will help increasing efficiencies.

Excess input use: Slack variables were also analyzed. A slack variable indicates excess of an input. A farm can reduce its expenditure on an input by the amount of slack variable without reducing its output. Mean input slacks and excess input use percentages are given in Table 7.

The greatest input excess in is labor use. Pesticide costs and machinery working hours follow this. According to these results, sample farms could reduce labor use by 38% staying at the same production level. Number of farms using excess labor is also high (31). Given the high population growth rate and high family sizes, excess labor use is not surprising. There are also other evidences supporting this result. As Oren *et al.* (2004) reports, despite the prevalence of off-farm working, one fourth of the labor is redundant in the region.

Excesses in machinery working time is also an expected result, given the small average farm size (8.6 ha) and mean plot numbers (1.6) of the farms. Use of machinery and labor is difficult and time consuming in small and scattered plots. This may form a major cause of inefficiency.

DEA analysis reports excess use for all inputs, especially for labor. SFA analysis shows a negative elasticity for fertilizer-N only.

Suggestions for further studies: This study reveals existence of technical efficiencies in wheat production in Southeastern Anatolia. However, allocative efficiencies are also important and should be studied. A more detailed study involving environmental variables may reveal the determinants of efficiency. These determinants may give a clearer picture of farm aspects that could be targeted in order to increase efficiency.

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