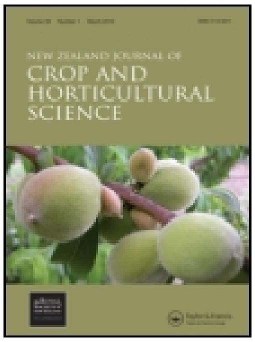

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Measuring the technical efficiency and determinants of efficiency of rice (*Oryza sativa*) farms in Marmara region, Turkey

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Abstract The objective of this study was to evaluate the technical and scale efficiency of sample rice (*Oryza sativa*) farms and subsequently identify determinants of technical inefficiency in the Balıkesir and Edirne provinces of Turkey. An input oriented data envelopment analysis (DEA) was used to estimate technical efficiency scores. Additionally, Tobit regression was used to explain the variation in the efficiency scores related to farm-specific factors. The data used in this study were based on a direct interview survey of 70 randomly selected rice farm households in the 2007 production year. Study results revealed that overall the technical efficiency score of sample rice farms was 0.92 on average and ranged from 0.75 to 1.00. Sample rice farms could reduce their inputs by c. 8% and still produce the same level of rice output. Calculated efficiency scores were subsequently regressed on explanatory variables using a Tobit analysis, to help in identifying inefficiency related factors. In this study, five explanatory variables were identified as being related to efficiency. The Tobit regression estimates showed that factors such as number of plots, farmer's age, and off-farm income negatively influenced technical efficiency, whereas farm size and membership of a cooperative showed a positive relationship with efficiency.

Keywords efficiency; data envelopment analysis; Tobit model; rice farms; Turkey

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INTRODUCTION

The agricultural sector of Turkey still accounts for a relatively large share of total output and employment compared with many other countries. The population of Turkey continues to increase rapidly. Therefore, to provide the nutritional needs of a highly growing population, agriculture still has great importance. It contributed c. 10% to the gross domestic product (GDP) and accounted for 26.4% of total employment in 2007. According to the last agricultural survey in 2001, there were c. 3 million farms in Turkey (TURKSTAT 2008). In addition, some agro-industrial sectors rely on agriculture through the processing of agricultural products.

Turkey has a major role among the major cereal producing countries in the world. Wheat, barley, rice (*Oryza sativa*), and maize are the main species of cereals produced in Turkey. Cereal production occupies 74% of Turkey's cropland (TURKSTAT 2008).

The rice area accounted for c. 0.8% of the total cereal area in 2006, but its share in the cereal area changes from year to year (TURKSTAT 2008). Although rice does not cover as much planted area in Turkey compared with other cereals, it provides high income for many families. In Turkey, the family-owned farm is the basic unit of agricultural production, and family members provide most of the farm labour. This situation explains well the socio-economic importance of rice farming in Turkey (Çetin & Tipi 1999).

Rice production in Turkey increased significantly over the last 3 years. The rice area is 99 100 ha with a production of 696 000 t and average yield of 7023 kg/ha. Milled rice production is 417 600 t for the 2006 production year. Rice production increased more than area because of higher yields, especially in the Thrace region, which had recorded high yields in 2006. Increase in production was mostly in the Osmancik variety, which competes directly with Calrose (TMO 2006; WTO 2007).

Although all geographical regions in Turkey are ecologically suitable for rice cultivation, and grain yield per unit area is higher than the world average, rice production in Turkey does not satisfy domestic demand. Average rice consumption per capita in Turkey is almost 8 kg. Total annual rice demand of the population of 70.5 million is 560 000 t whereas rice production is 417 600 t (TMO 2006). Since total rice consumption is higher than the total rice production, rice is imported. To increase both the amount of rice growing areas and rice yield, beside legal policies, there is a need for sustainable agricultural plans, efficient management practices, and efficient inputs by farmers.

The main rice growing provinces in Turkey are Edirne, Samsun, Çorum, Balıkesir, Çanakkale, Sinop, Kastamonu, and Diyarbakır. Edirne province, which is located in Thrace region, has the largest production area. Edirne and Balıkesir provinces, which were chosen for this study, accounted for c. 54% of rice production of Turkey in 2006 (TURKSTAT 2008).

Owing to the socio-economic importance of rice farming in these provinces and in Turkey overall, efficiency studies play an important role in determining alternative policies. Moreover, the result of these analyses can be used for sustainable agricultural planning.

The main purpose of this study was to measure technical efficiency and investigate factors affecting technical inefficiency of rice production at the farm level in Turkey.

The measurement of technical efficiency or inefficiency in the agricultural sector of developing and developed countries has received renewed attention since the late 1980s from an increasing number of researchers. Also, development and agricultural economists have examined the sources of productivity growth over time and of productivity differences among countries and regions over this period. This is most likely driven by the development of new empirical techniques and a desire to assess the degree to which the applied agricultural policies have improved agricultural productivity in developing countries. The frontier approaches such as the stochastic frontier analysis (SFA) and data envelopment analysis (DEA) to efficiency and productivity measurement have become more popular (Tipi & Rehber 2006). The former uses econometric methods whereas the latter uses linear programming.

A commonly held view in previous studies is that the use of the Tobit model can handle the characteristics of the distribution of efficiency measures and thus provide results that can guide policies to improve performance. DEA efficiency measures obtained in the first stage are the dependent variables in the second stage Tobit model.

This study sets out to analyse technical efficiency of rice farms in Turkey, and to identify farm-specific characteristics that explain variation in the efficiency of the farmers. An understanding of these relationships could provide policymakers with information to design programmes that can contribute to measures needed to expand the rice production potential of Turkey.

Technical efficiency is defined as the ability of a farm to either produce the maximum possible output from a given bundle of inputs and a given technology, or to produce a given level of output from the minimum amount of inputs for a given technology. The existence of persistent technical inefficiencies over time offers an opportunity to reduce inputs without reducing outputs, or to increase output from the same amount of input (De Koeijer et al. 2002).

Estimation of technical inefficiency does not have much policy implication by itself. The methods explained until now try to determine the relationship between input use of farms and their output. However, they do not give any explanation about the reasons for inefficiency. The explanation of inefficiency by quantitative methods has been an important area of research. The general idea behind the applied work about the explanation of inefficiency is related to the existence of farm specific variables that are assumed to affect the efficiency of the farm (Battese & Coelli 1995).

Analysis performed this way goes beyond much of the published literature concerning efficiency because much research in this area of productivity analysis focuses exclusively on the measurement of technical efficiency (Bravo-Ureta & Pinheiro 1993; Coelli 1995).

METHODOLOGY

This study uses a two-step approach. In the first step, the DEA model is used to measure technical efficiencies of farms as an explicit function of discretionary variables. In the second step, farm-specific variables that are assumed to affect the efficiency of the farm are used in a Tobit regression framework to explain variations in measured inefficiencies. Therefore, we first provide a brief description of the DEA and Tobit models.

Data envelopment analysis

Data envelopment analysis (DEA) is a mathematical technique, based on linear programming (LP), which is used to measure the relative efficiency of decision-making units with multiple inputs and multiple outputs. DEA is one of several techniques that can be used to calculate a best practice production frontier (Helfand & Levine 2004).

Coelli (1995) indicated that the DEA approach has two main advantages in estimating efficiency scores. First, it does not require the assumption of a functional form to specify the relationship between inputs and outputs. Second, it does not require the distributional assumption of the inefficiency term.

The measure of technical efficiency that Farrell (1957) introduced is an input oriented measure—by how much inputs could be reduced while maintaining the existing level of output. The alternative way in which to consider technical efficiency is an output oriented measure—by how much could output be increased while using the given level of inputs. The measure of technical efficiency (input and output orientated) has subsequently been extended to accommodate multiple inputs and outputs. This approach to measuring technical efficiency yields a relative measure. It measures the efficiency of a farm relative to all other farms in a sample. Farrell argued that this is more appropriate as it compares a farm's performance with the best actually achieved rather than with some unattainable ideal (Fraser & Cordina 1999).

Technical efficiency is considered for the optimal combination of inputs to achieve a given level of output (an input-orientation) or the optimal output that can be produced given a set of inputs (an output-orientation). This analysis is focused on input-oriented models, where the decision-making units' ability to consume the minimum input given the level of outputs that should be attained is considered. The input-orientation is more appropriate in this instance because the output level is given by the target of rice production, which should reach the self-sufficient level (zero imports). The decision on the orientation of DEA models is also supported by considering the degree of a farmer's control over variables in the decision-making unit's production mix (rice farm). Rice farmers have more control over their inputs than their outputs. Therefore, as in other agricultural productivity studies (Wadud & White 2000; Krasachat 2004; Brázdik 2006), the input-oriented DEA model is used in this study.

According to Coelli et al. (1998), the constant return to scale (CRS) DEA model is only appropriate when all firms are operating at optimal scale. Imperfect competition or constraints on finance may cause a firm to not operate at optimal scale. For this reason, an input-oriented variable return to scale (VRS) DEA model is used to calculate technical efficiency in this study. By allowing for variable return to scale our measure of technical efficiency can be split into pure technical efficiency and scale efficiency.

An input oriented VRS DEA model is given below for N decision-making units, each producing M outputs by using K different inputs (Coelli et al. 1998):

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta \\
&\text{st } -y_i + Y\lambda \le 0 \\
&\quad \theta x_i - X\lambda \ge 0 \\
&\quad N1'\lambda = 1 \\
&\quad \lambda \ge 0
\end{aligned}
$$

where θ is a scalar λ is a $N\times1$ vector of constants and $N1$ is an $N\times1$ vector of ones. The value of θ obtained will be the efficiency score for the i-th decision-making unit. It will satisfy $\theta\le1$, with a value of 1 indicating a point on the frontier and hence technically efficient decision-making unit, according to the Farrell (1957) definition. Thus, the linear programming problem needs to be solved N times and a value of θ is provided for each farm in the sample.

Because the VRS DEA model is more flexible and envelops the data in a tighter way than the CRS DEA, the VRS DEA efficiency score is equal to or greater than the CRS score. Using the relationship between VRS and CRS DEA scores, the scale efficiency (SE) score for a farm is computed (Dhungana et al. 2004) as:

$$SE_i = \frac{TE_{i,CRS}}{TE_{i,VRS}}$$

where $SE_i = 1$ indicates a scale efficient farm that is operating at a point of CRS. A value SE<1 indicates scale inefficiency. However, scale inefficiency can be the result of the existence of either increasing or decreasing return to scale. This may be determined by calculating an additional DEA problem with non-increasing returns to scale imposed. This can be conducted by changing the VRS DEA model by replacing the $N1'\lambda = 1$ restriction with $N1'\lambda \leq 1$. If the non-increasing returns to scale TE score is unequal to the VRS TE score, it indicates that increasing return to scale (IRS) exists for that farm. If they are equal, then decreasing return to scale (DRS) applies.

Tobit model

It is also of considerable interest to explain DEA efficiency scores by investigating the determinants of technical efficiency. As defined above, the DEA score falls between the interval 0 and 1—making the dependent variable a limited dependent variable. A commonly held view in previous studies is that the use of the Tobit model can handle the characteristics of the distribution of efficiency measures and thus provide results that can guide policies to improve performance. In recent years, many DEA applications use a two-stage procedure involving both DEA and Tobit. DEA efficiency measures obtained in the first stage are the dependent variables in the second stage Tobit model.

The goal of the second stage is to explore relationships between the technical efficiency measure and other relevant variables such as farm size, number of plots, farmer's age, and off-farm income.

The Tobit model was first suggested in the econometrics literature by Tobin (1958). These models are also known as truncated or censored regression models (the model is truncated if the observations outside a specified range are totally lost and censored if one can at least observe the exogenous variables) where expected errors do not equal zero. Therefore, estimation with an ordinary least squares (OLS) regression of DEA scores would lead to a biased parameter estimate since OLS assumes a normal and homoscedastic distribution of the disturbance and the dependent variable (Maddala 1983; Amemiya 1984).

The standard Tobit model can be defined as follows for observation (farm) i:

$$y_i^* = x_i'\beta + u_i \qquad i = 1,2,\ldots,n,$$
$$y_i = y_i^* \text{ if } y_i^* < 0$$
$$y_i = 0, \text{ otherwise}$$

where $u_i \sim N(0,\sigma^2)$, x_i and β are vectors of explanatory variables and unknown parameters, respectively. The y_i^* is a latent variable and y_i is the DEA score (Amemiya 1984).

Data and the specification of variables

The data used in this study were based on a direct interview survey of 70 randomly selected rice farm households in two provinces of the Marmara region of Turkey. The selected provinces were Balıkesir and Edirne. These are predominantly rice producing areas. The data were for the 2006 normal rice growing season.

One output and six inputs were used in the DEA model. The only output is the rice yield per farm. The inputs are land (ha), chemical costs, fertiliser costs, seed costs, total labour used (h/farm) in rice farming from land preparation through harvest (both family and hired labour), and other cash costs (value of cash expenditures on machinery for ploughing and harvesting). Table 1 gives the descriptive statistics of the inputs and output.

After calculating DEA scores, a Tobit regression was used to determine causes of inefficiencies. The variables most commonly used in previous studies to explain the efficiency of a sample farm were size, age of operators, experience of farmers, education level of farmers, use of extension services, data recording, credit use, and combination of inputs (Phillips & Marble 1986; Kalirajan & Shand 1989; Bravo-Ureta & Evenson 1994; Parikh et al. 1995; Ahmad & Bravo-Ureta 1996; Lewelyn & Williams 1996; Seyoum et al. 1998; Amara et al. 1999; Sharma et al. 1999; Wilson et al. 2001; Trip et al. 2002; Iraizoz et al. 2003; Dhungana et al. 2004; Bozoğlu & Ceyhan 2007).

In this study, the explanatory variables were obtained from the sample farms by questionnaire. The variables used in this study to explain the efficiency/inefficiency of a sample farm were size, number of plots, farmers' age, off-farm income, and membership of cooperative.

Farm size was measured in hectares. Plot number was included as a variable to reveal the relationship between land fragmentation and technical efficiency. The age variable included in the inefficiency model served to test the hypothesis that younger farmers were more receptive to innovations. To explore the relationship between technical efficiency and the existence of off-farm income, the off-farm income variable was a dummy. It equalled 1 for off-farm income and 0 otherwise. Membership of a cooperative was the other dummy variable. It equalled 1 if farmers were members of a cooperative and 0 otherwise.

DEA scores were estimated using the computer program DEAP 2.1 developed by Coelli (1996). Efficiency scores of the farms were calculated under constant return to scale (CRS) and variable return to scale (VRS) assumptions.

Maximum likelihood estimates of the parameters for the Tobit regression were obtained by using the computer program LIMDEP v.7.0.

RESULTS AND DISCUSSION

In this study, an input-oriented DEA model was used for estimating overall technical (TE_{CRS}), pure technical (TE_{VRS}), and scale efficiencies for the rice farms (Table 2). The mean values of overall technical, pure technical, and scale efficiency were 0.92, 0.94, and 0.98, respectively.

Overall technical efficiency score of rice farms in the studied area was 0.92, on average. This means that, on average, rice farms within the studied area could reduce their inputs by c. 8% and still produce the same level of rice output. The splitting of the technical efficiency measure produced estimates of 6% pure technical inefficiency and 2% scale inefficiency (Table 2). By eliminating scale inefficiency, the farms can increase their average technical efficiency level from 0.92 to 0.94.

Rice farms showed different returns to scale characteristics (Table 3). Of the 70 farms, 38 showed constant returns to scale, 18 showed variable returns to scale, and 14 showed increasing returns to scale.

Scale efficiency indicates whether any efficiency can be obtained by improving the size of the operation. For the studied rice farms, scale efficiency is quite high, with an average of 0.98 indicating that the majority of farms are operating at or are near to their optimal size.

In relation to this, the returns to the scale section of the table indicates the number of farms experiencing increasing or decreasing returns to scale, or that are at their optimal size. If farms experience increasing returns to scale they will benefit by becoming larger, whereas decreasing returns indicate the opposite. Similarly, if farms are at their optimal size, they would suffer losses in efficiency from changing their scale of production.

Table 1 Descriptive statistics of the inputs and output for the sample farms. (Source: field survey.)

Variables	Unit	Mean	SD	Min.	Max.
Outputs					
Rice yield	kg/farm	44654.86	53764.96	1260.00	240000.00
Rice yield	kg/ha	6960.00	584.68	6000.00	8000.00
Inputs					
Land	ha	6.18	7.01	0.20	30.00
Chemicals	TL/farm	850.10	906.20	23.80	4750.00
Fertilisers	TL/farm	1897.06	1952.04	61.60	8025.00
Seed	TL/farm	2300.50	2950.62	60.00	12600
Labour	h/farm	1472.23	1679.28	83.32	7743.00
Other cash costs	TL/farm	10940.44	12559.62	251.70	54331.50
Farm-specific factors					
Age	years	43.84	6.65	28.00	58.00
Farm size	ha	6.18	7.01	0.20	30.00
No. of plots/farm	no.	2.74	2.01	1.00	13.00
Off-farm income*	dummy	0.14	0.35	0.00	1.00
Membership of cooperative†	dummy	0.84	0.37	0.00	1.00

*It equalled 1 for off-farm income and 0 otherwise.
†It equalled 1 if farmers were members of cooperative and 0 otherwise.

Table 2 Data envelopment analysis (DEA) scores of technical, scale, and pure technical efficiencies for rice (*Oryza sativa*) farms. (Source: DEA scores were calculated using the computer program DEAP 2.1 developed by Coelli (1996).)

	Mean	SD	Min.	Max.
Overall technical efficiency	0.92	0.07	0.75	1.00
Pure technical efficiency	0.94	0.07	0.77	1.00
Scale efficiency	0.98	0.03	0.88	1.00

For returns to scale, the 14 farms recording increasing returns to scale indicates that farms would improve their efficiency of resource use by increasing in size. But a high level of scale efficiency indicates little scope for improvement in farm size to increase efficiencies.

In general, the cause of inefficiency may have been either inappropriate scale or misallocation of resources. Inappropriate scale suggests that the farm is not taking advantage of economies of scale, whereas misallocation of resources refers to inefficient input combinations. In this study, scale efficiencies were relatively high; therefore, it seems that efficiencies were mainly because of improper input use (Ören & Alemdar 2006).

The estimates of the Tobit regression coefficients and marginal effects of the explanatory variables on technical efficiency are shown in Table 4. It is important to note that the dependent variable in the model is the VRS DEA efficiency score. A positive coefficient implies an efficiency increase whereas a negative coefficient means an association with an efficiency decline. The results of the regression are significant at the 90% level or higher. Marginal effect of the Tobit model is calculated to be 69.58%. The computations were conducted by LIMDEP 7.0.

Based on the results of the efficiency model, all farm-specific factors had a significant coefficient. Most of the signs related to efficiency determinants were as expected. The parameter estimates showed that factors such as number of plots, farmer's age, and off-farm income negatively influenced technical efficiency, whereas farm size and membership of a cooperative showed a positive relationship with efficiency (Table 4).

Table 3 Summary of returns to scale results ($n = 70$). (CRS, constant return to scale; DRS, decreasing return to scale; IRS, increasing return to scale.)

Characteristics	No. of farms	Mean farm size (ha)	Mean output (kg/ha)
CRS	38	8.22	7090.8
DRS	18	5.96	7023.5
IRS	14	0.89	6525.0

Table 4 Estimations of tobit regression coefficients and marginal effects. (Huber/White SEs of estimates are shown in parentheses.)

Variables	Coefficients	Marginal effects
Constant	1.207073 $P < 0.01$	
	(0.078768)	–
Farm size (ha)	0.000271 $P < 0.1$	
	(0.000143)	0.0001885
No. of plots (no.)	–0.009844 $P < 0.05$	
	(0.004292)	–0.006849
Age (years)	–0.005905 $P < 0.01$	
	(0.001618)	–0.0041
Off-farm income (dummy)	–0.130991 $P < 0.01$	
	(0.027346)	-0.0912
Membership of cooperative (dummy)	0.048486 $P < 0.05$	
	(0.023515)	0.0337
Sigma	0.0780	
(disturbance SD)	(0.0078)	
R-squared	0.278994	
Adjusted R-squared	0.210327	
Sum squared residuals	0.218490	
Log likelihood	31.24029	
Akaike info criterion	–0.692580	

Farm size coefficient indicated that the large farms were more technically efficient than the small ones. According to some researchers, there was a positive relationship between farm size and efficiency (Pinherio 1992; Curtis 2000; Morrison 2000; Latruffe et al. 2002; Kamruzzaman et al. 2006; Bozoğlu & Ceyhan 2007), whereas others reported the opposite (Lau & Yotopoulos 1971; Sidhu 1974; Huang & Bagi 1984; Squires & Tabor 1991).

One of the significant findings of this study was that the most important determinant of inefficiencies is the fragmented structure of farmlands. Fragmentation of farmlands had a negative effect on technical efficiency, as expected. Land fragmentation causes a loss of farmland area because land is used for marking boundaries and a low efficiency in irrigation water management because of the irregular shape of numerous plots. It also causes time loss in travel and inconvenience in agricultural management.

Farmer's age may have both a positive and a negative impact on technical efficiency, depending on whether older farmers are more experienced or slower to accept new technologies than young farmers. The age coefficient indicated that the younger farmers were more efficient than the older ones. This finding confirmed the results of previous studies conducted by Battese & Coelli (1995), Mathijs & Vranken (2000), and Bozoğlu & Ceyhan (2007). This result could be explained by older farmers being more likely to have contacts with extension agents and being less willing to adopt new practices and modern inputs.

Another outcome of the efficiency model was the negative and significant effect of off-farm income on technical efficiency. The farm family without off-farm income was more efficient than the farm family having off-farm income. The productive effects of having an off-farm income are difficult to explain theoretically. But having off-farm incomes could imply less time on the farm and possibly less efficient use of resources.

The coefficient of the cooperative membership variable was positive, implying that farmers who belonged to cooperatives are more efficient. This expected result could be explained by technical assistance to the farmers, information sharing, and training courses by cooperatives.

The marginal effect coefficients of farm size and membership of a cooperative were found to be 0.018% and 3.37% with a positive effect on technical efficiency, respectively. Farm size would reduce inefficiency by 0.018% if it increases 1 unit. Being a cooperative member would increase efficiency by 3.37%.

The marginal effect coefficients of the number of plots, farmer's age, and off-farm income was found to be 0.68%, 0.41%, and 9.12% with a negative effect on technical efficiency, respectively. The number of plots and farmer's age would increase efficiency by 0.68%, 0.41% if they reduce 1 unit, respectively. Off-farm income would reduce efficiency by 9.12% (Table 4).

CONCLUSIONS

The objective of this study was to apply a two-step methodology to investigate the technical efficiency and assess the factors affecting the efficiency of rice farms in Turkey. The lack of empirical studies in Turkey, which focus on the efficiency and the factors affecting the efficiency of the rice farms, motivated this study.

The analysis of technical efficiency scores reveals that rice farmers could benefit from the adoption of the best practice methods of production because the results indicate a range of differences in efficiency across farms. On average, the analysed farms were relatively inefficient with the potential for reducing their inputs 8% to produce the same amount of rice. Splitting the technical efficiency into pure technical efficiency and scale efficiency, it can be concluded that the majority of farms operate at or close to full-scale efficiency. So, farmers that are operating technically inefficiently are doing so because they use technically inefficient production mixes rather than because of the size of their operations.

The second stage analysis attempted to explain variations in efficiencies between rice farms. The analysis of the factors associated with the calculated technical efficiency score using the Tobit regression indicates what aspects of the considered rice farms could be targeted to improve efficiency. The parameter estimates showed that factors such as number of plots, farmer's age, and off-farm income negatively influenced technical efficiency, whereas farm size and membership of a cooperative showed a positive relationship with efficiency.

As a result of the study, policy makers should focus on farmers' training and extension programmes to reduce technical inefficiency of rice farms. Crop management practices for all areas should be determined and provided to the farmers in an efficient way.

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