D.E.Ü.İ.İ.B.F.Dergisi
Cilt:18 Sayı:1, Yıl:2003, ss: 71-92

THE COMPARASION OF DEA AND SFA METHODS IN THE EFFICIENCY OF THE TURKISH MANUFACTURING INDUSTRY

A. Özlem ÖNDER(*), Ertuğrul DELIKTAŞ(*), Metin KARADAĞ(*)

ABSTRACT

The main aim of this paper is to compare data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods by estimating technical efficiency in the manufacturing industry in the selected provinces of Turkey by using panel data for the period 1990-1998. The comparison of the efficiency scores obtained from these two methods show that there is a significant difference in ranking of provinces in respect of the two methods, and average firm size and regional agglomeration have an impact on efficiency.

Key words: *Technical efficiency, stochastic production frontier, data envelopment analysis, Turkish manufacturing industry.*

1. Introduction

In recent years, there have been a considerable number of studies dealing with productivity in the manufacturing sector (see, for example, Uygur, 1990; Krueger and Tuncer, 1982; Zaim and Taşkın, 1997; Yıldırım, 1989; and Önder and Lenger 2000). However, there appears to be a few studies concerning technical efficiency in that sector as far as Turkey is concerned. (see Taymaz and Saatçi, 1997; Zaim and Taşkın, 2001; Balcılar and Çokgezen, 2001). To the authors' best knowledge, no efficiency study in manufacturing industry is conducted at the regional level by using the data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods and comparing the results obtained from these two

(*)Department of Economics, Ege University, Izmir / Turkey.

methods as far as Turkey is concerned. In this study, we use both methods because they have their respective advantages and disadvantages.[1] We also subdivide the manufacturing industry into public and private sectors in order to make some comparison between these two sectors. This is important because the public enterprises are being blamed for absorbing the government's revenue and are being held responsible for some economic problems in Turkey (see also Zaim and Taşkın, 1997).

Thus, the main objective of this study is to estimate technical efficiency in manufacturing industry in selected provinces in Turkey by using DEA and SFA[2]. In order to do so, we have used panel data of the 18 selected provinces in Turkey over the period 1990-1998[3]. We compare the results obtained from the two techniques in estimating technical efficiency. The major issues considered in this study include (1) giving the idea behind why we employed these two methods for the aim of the study (2) comparing efficiency performance among the provinces and as well as across the public and private sector as far as manufacturing industry in the provinces is concerned.

The remainder of this paper is organised as follows. Section two provides a discussion of the methodology. The data and variable definitions are explained in section three. Evaluation of the results are summarised and discussed in section four. The paper concludes with a summary analysis of the findings in section fives.

2. Methodology

SFA and DEA are the two alternative methods for estimating frontier functions and thereby measuring efficiency in production. DEA uses linear programming, whereas stochastic frontiers use econometric methods. These two alternative methods have different strengths and weaknesses.

---

[1] Strengths and weaknesses of these two methods are discussed in detail in Kalirajan and Shand, 1999; Fried *et al.*, 1993; and Reinhard *et al.*(2000)

[2] Although there are other techniques such as DFA used in the literature, stochastic frontier analysis (SFA), and data envelopment analysis (DEA) are alternative analytical techniques designed to measure the efficiency of producers.

[3] The names of these provinces and the regions they belong to are given in section three of the study.

A major advantage of DEA is that it places no restrictions on the functional form of the production relationships between inputs and outputs, and does not require imposition of any distributional assumption on inefficiency term. Also, DEA can accommodate multiple inputs and multiple outputs simultaneously. On the other hand, one of the main disadvantages of DEA is that it can be extremely sensitive to variable selection and data errors (Seiford, 1996).

With regard to SFA, various hypotheses concerning modelling the technology, and characteristics of firm-specific efficiency measures can be statistically tested. But, a major criticism against SFA is that it requires the imposition of a certain specific distributional assumption on firm-specific technical inefficiency term. Although statistical testing procedures are available, they are all based on nested testing hypotheses (Kalirajan and Shand, 1999).

Singh *et al.* (2000) points out that the choice of methodology may have significant effect upon the results obtained. Therefore, they promote to use of both method in applied studies in order to be sure about the robustness of the results. In recent years, these two methods have been used together by several researches to measure efficiency in production (see, for example, Wadud and White, 2000; Reinhard *et al.,* 2000; Drake, 2001; Sharma *et al.*, 1997; and Cooper *et al*., 1995; Deliktaş and Balcılar, 2002).

2.1. Stochastic Frontier Analysis and the Model

Since stochastic frontiers production models were proposed by Aigner *et al.*, (1977), and Meeusen and van den Broeck (1977), there has been a vast range of application in the literature[4]. The model was originally defined for an analysis of cross-sectional data, but various models to account for panel data have been introduced by Pitt and Lee (1981), Cornwell *et al.* (1990), and Kumbhakar (1990).

Battese and Coelli (1995) proposes a stochastic frontiers production function for panel data, in which firm effects were assumed to be distributed as truncated normal random variables. Their model specifies the inefficiency effects as being directly influenced by number of explanatory variables. Also they permit the technical efficiency to vary systematically with time in their model.

One can say that the use of panel data has some advantages over cross-sectional data in the estimation of stochastic frontiers models. The application with

[4] See, for example, Greene (1993) and Coelli *et al.*, (1998) for the detailed literature survey.

panel data increases the number of degrees of freedom for estimation of parameters. (see Coelli *et al.* 1998, p 202).

In this paper, based on the panel data for the 18 selected provinces of Turkey for the period 1990-1998, we specify a translog stochastic production function by using the time-varying inefficiency model developed by Battese and Coelli (1995) in order to measure the technical efficiency in public and private manufacturing industries of the selected provinces.

The translog production frontiers defined by

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{3} \beta_k \ln x_{kit} + (1/2) \sum_{j=1}^{3} \sum_{k=1}^{3} \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_{k=1}^{3} \beta_{k4}\, t \ln x_{kit} +$$

$$\beta_4 t + \beta_{44} t^2 + v_{it} - u_{it}, \qquad i = 1,2,\ldots,N; \; t = 1,2,\ldots.T \qquad (1)$$

where, y_{it} denotes the production. The subscripts i represent the *i-th* manufacturing industry, which is subdivided into public and private sectors, thus, N is equal to 36 accordingly, whereas t represents year and T is equal to 9. Subscripts k and j index inputs. x_1 is the labour, x_2 represents capital and x_3 represents raw material. The β's are unknown parameters to be estimated. The v_{it}'s are random errors and assumed to be independently and identically distributed as $N(0,\sigma_V^2)$. They are also assumed independently distributed of the u_{it}'s that are technical inefficiency effects and are non-negative random variables. The u_{it}'s are assumed to be independently distributed. The distribution of u_{it} is obtained by truncation at zero of the normal distribution with mean m_{it} and variance σ_u^2, where m_{it} is defined by technical inefficiency associated with;

$$m_{it} = \delta_0 + \sum_{j=1}^{3} \delta_j z_{jit} \quad , \qquad (2)$$

where the $z's$ are explanatory variables, z_1 represents natural logarithm of average firm size which is measured as number of employee divided to number of firms. A positive coefficient of z_1 will support the hypothesis that the small size plants are more efficient than large size plants. z_2 , which is named as region, is defined as the ratio of output of a province to the total output. We have this variable in order to capture the effects of agglomeration and urbanization externalities[5] (see also, Taymaz and Saatçi, 1997). We expect a negative coefficient for this variable in Equation 2 if there are regional agglomeration and urbanization externalities in industries. z_3 represents time trend, and specifies that the inefficiency effects may change linearly with respect to time (see Battese and Coelli, 1995). The δ parameters are unknown to be estimated.

Technical efficiency of the *i*-th industry at *t*-th period of observation defined by

$$TE_{it} = \exp(-u_{it}). \tag{3}$$

2.2. Data Envelopment Analysis and the Model

The DEA method was developed by Charnes *et al*. (1978). Since then, there has been a large literature about the application of DEA methodology. Charnes *et al.* (1995) and Seiford (1996) give the comprehensive review of this method. Panel data applications of DEA method are also widely used in the literature (see for example, Millán and Aldaz, 2001; and Singh *et al.*, 2000).

The output-oriented DEA model for a single output used in this study is closely related to Coelli *et al.* (1998 p 158). The model can be formalized as follows. Consider the situation for the N industries, each producing a single output by using K inputs. For the i-th industry $\mathbf{x_{it}}$ is a column vector of inputs, while y_{it} is a scalar representing the output. **X** denotes the $K \times NT$ matrix of inputs and **Y** denotes $1 \times NT$ matrix of output. The variable returns to scale (VRS) output-oriented DEA model is given by;

[5] The importance of agglomeration mentioned in some regional studies such as Driffield and Munday (2001), and Dascher (2002)

$$\max_{\phi,\boldsymbol{\lambda}} \phi \tag{4}$$

subject to

$$-\phi\ y_{it} + \mathbf{Y}\boldsymbol{\lambda} \geq 0,$$

$$\mathbf{x_{it}} - \mathbf{X}\boldsymbol{\lambda} \geq 0,$$

$$\mathbf{N1}'\ \boldsymbol{\lambda} = 1,$$

$$\boldsymbol{\lambda} \geq 0,$$

where $1 \leq \phi < \infty$, **N1** is a $1 \times NT$ vector of ones, λ is a $NT \times 1$ vector of weights. $1/\phi$ defines technical efficiency score, which varies between zero and one, with a value of one indicating any point on the frontier. Constant returns to scale (CRS) output-oriented DEA model is obtained through eliminating the constraint $\mathbf{N1}'\ \boldsymbol{\lambda} = 1$. The linear programming problem must be solved *NT* times in order to provide a value of ϕ for each industry in the sample.

3. Data

The data set related to manufacturing industry of each province were obtained from several issues of Annual Manufacturing Industry Statistics, published by State Institute of Statistics (SIS). The data set covers the public and the private sector establishments, which employ ten or more workers. Investment deflators for the private and public manufacturing industries were taken from several issues of Main Economic Indicators published by SPO. Manufacturing industry wholesale price index was taken from several issues of Monthly Bulletin of Wholesale Price Index, published by SIS.

The data set employed in this study covers 18 provinces in Turkey over the 1990-1998. Table 1 gives the regional location of the provinces and their percentage share in total value added created in the Turkish manufacturing sector.

Table 1. The Regional Location of the Provinces and Their Percentage Share in Total Value Added

Region	Provinces*
Marmara	Istanbul (24.8), Kocaeli (15.3), Bursa (6.4), Tekirdag (3.3), Kırklareli (1.2), Balikesir (0.9)
Aegean	Izmir (12.1), Denizli (1.3), Manisa (1.8),
Black Sea	Zonguldak (3.9), Bolu (1.0),
Central Anatolia	Ankara (6.4), Kayseri (1.5), Konya (1.3), Eskisehir (1.3)
South East Anatolia	Gaziantep (0.9)
Mediterranean	Icel (3.2), Adana (2.9)

*The percentage share of province in total value added created in Turkish manufacturing industry is given in parentheses

As can be seen from the table, the overall value added created in the manufacturing industries in these provinces constitutes approximately 90% of the value added created in the Turkish manufacturing industry in total. We should mention that the data related to new provinces that were formerly affiliated as a town to a province were included in the associated provinces in order to obtain comparable results.

Summary statistics of the data is presented in Table 2 in two parts. Panel A shows the summary statistics for the manufacturing industry related to the production function, while Panel B presents the summary statistics of inefficiency effects.

Table 2. Characteristics of the data set (324 observation)

A. Variables in Production Function

		Output (1981 prices) *	Labour (hours)	Capital (1994 prices)*	Raw Material, (1981 prices)*
	mean	83,346	9,589,596	9,281,906	39,993
Public	stnd,dev	128,453	9,683,726	12,509,144	61,162
	minimum	326	74,240	6,083	215
	maximum	477,225	43,122,992	54,826,202	242,285
	mean	370,077	74,678,888	38,441,858	228,849
Private	stnd,dev	575,058	117,015,721	59,249,074	356,014
	minimum	31,638	7,080,814	1,042,193	21,353
	maximum	2,882,782	592,389,721	321,010,275	1,783,639
	mean	226,711	42,134,242	23,861,882	134,421
Total	stnd,dev	440,086	89,074,792	45,177,684	272,003
	minimum	326	74,240	6,083	215
	maximum	2,882,782	592,389,721	321,010,275	1,783,639

B. Inefficiency Effects

		Averagesize	Region
	mean	660	.048
Public	stnd.dev	532	.061
	minimum	11	.010
	maximum	3,603	.290
	mean	116	.048
Private	stnd.dev	178	.061
	minimum	50	.010
	maximum	2,320	.290
	Mean	388	.048
Total	stnd.dev	481	.061
	minimum	11	.010
	maximum	3,603	.290

*million Turkish Lira

As can be seen from Panel A in Table 2, the size of manufacturing industry in public sector is around one fourth of private manufacturing industries on average. This ratio is valid for output and inputs values on average except for labour. Output, is measured in value terms at constant 1981 prices. Inputs used in our model are labour, capital, and raw materials. Labour is measured as total number of hours worked in production, while the raw material includes expenditures on output, supplementary materials, packaging materials and the other raw materials required for production. Raw materials are measured in value terms at constant 1981 prices. However, data for physical capital stock were not available. Therefore, the capital input was calculated through perpetual inventory method (see Önder and Lenger, 2000 for details)[6]. Regarding inefficiency effects, average firm size in public sector is bigger than the one in private sector on average as can be seen from Panel B.

4. Results

4.1. Results of Estimation

The maximum-likelihood estimates for the parameters of the stochastic frontiers model are estimated by using a computer program FRONTIER 4.1 written by Coelli (1996a), where the variance parameters are expressed in terms of $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma_s^2$. Table 3 presents parameter estimates for the model defined by equations (1) and (2), which constitutes Model 1.

Table 3. Stochastic Production Frontier Estimation Results

Variable	Parameter	Model 1	Model 2
Constant	β_o	11.062*	11.168*
		(5.046)	(6.545)
ln(labour)	β_1	-1.406*	-1.505*
		(-3.211)	(-4.066)
ln(capital)	β_2	-1.330*	-1.231*
		(-6.235)	(-6.437)
ln(raw material)	β_3	3.214*	3.202*
		(9.148)	(10.191)
Year	β_4	0.010	-0.009
		(0.122)	(-0.348)
$[\ln(\text{labour})]^2$	β_{11}	0.195*	0.213*
		(3.479)	(4.128)

[6] When using total horsepower of installed equipment as a proxy for capital, we obtained similar results.

(Continued)

$[\ln(\text{capital})]^2$	β_{22}	0.083*	0.084*
		(4.509)	(4.751)
$[\ln(\text{raw mat.})]^2$	β_{33}	0.177*	0.171*
		(4.373)	(4.171)
$(\text{Year})^2$	β_{44}	0.33E-03	0.001
		(0.159)	(0.254)
ln(labour)xln(capital)	β_{12}	0.036	0.023
		(1.339)	(0.947)
ln(labour)xln(raw mat.)	β_{13}	-0.215*	-0.218*
		(-6.033)	(-6.371)
ln(capital)xln(raw mat.)	β_{23}	-0.048	-0.038
		(-1.801)	(-1.521)
ln(labour)x(Year)	β_{14}	-0.007	0
		(-0.775)	
ln(capital)x(Year)	β_{24}	0.004	0
		(0.618)	
ln(raw mat.)x(Year)	β_{34}	0.004	0
		(0.445)	
Inefficiency Effects			
Constant	δ_0	0.166	0.130
		(0.952)	(0.730)
ln(average size)	δ_1	0.052*	0.052*
		(2.187)	(2.278)
Region	δ_2	-5.392*	-5.069*
		(-2.471)	(-2.519)
Year (time trend)	δ_3	-0.018	-0.144
		(-1.060)	(-0.866)
Variance Parameters			
σ_s^2		0.054*	0.053*
		(7.371)	(8.942)
γ		0.418*	0.377*
		(2.935)	(3.217)
Log-likelihood		42.182	41.646

Notes: t-values are in parentheses *significant at 5% level.

Table 4 presents the results of formal hypotheses tests. The null hypotheses test the assumptions imposed on the data and the equations (1) and (2) for the Model 1[7].

Table 4. Hypothesis Tests

Null Hypothesis	Log-likelihood[a]	Test Statistic	Critical value[b]	Decision
Cobb-Douglas production function All β_{ij} =0	-5.25	94.86	18.31	Reject H_0
No inefficiency $\gamma=\delta_0=\delta_1=\delta_2=\delta_3=0$ [c]	29.13	26.10	10.37	Reject H_0
Hicks-neutral technical change $\beta_{14}=\beta_{24}=\beta_{34}=0$	41.65	1.06	7.81	Accept H_0

a. Log-likelihood value under null hypothesis
b. Critical value of the test statistic at the 5 % level of significance
c. If the null hypothesis, there are no technical inefficiency effects in the model, is true, then the generalized likelihood-ratio statistic is asymptotically distributed as a mixture of chi-square distribution (Table 1, Kodde and Palm,1986).

As can be seen from Table 4, the first null hypothesis, which specifies that the Cobb-Douglas production function is an adequate representation (all second order coefficients, β_{ij}, are zero) was rejected. If the second null hypothesis, which specifies that there is no inefficiency effects ($\gamma=\delta_0=\delta_1=\delta_2=\delta_3=0$) is true, then the model will be equivalent to the average response function, and thus it can be estimated by the ordinary least squares method. However, this hypothesis was rejected. On the other hand, the hypothesis about neutral technical change was accepted. Regarding these results, we re-estimated the translog production function with neutral technical change (see Model 2 in Table 3).

[7] All of the hypotheses tests were obtained using the generalized likelihood-ratio statistic, which is defined as $\lambda=-2\ln[L(H_0)/L(H_1)]$, where $L(H_0)$ and $L(H_1)$ are the value of the likelihood function for the frontiers model under the null and alternative hypothesis, H_0 and H_1, respectively.

As can be seen from Table 3, most of the coefficients of Model 2 are significant suggesting that the model is a good fit. The estimated variance parameter γ is found to be significant indicating that technical inefficiency effects have an impact on output. This result is in line with Wadud and White (2000), and Battese and Coelli (1995).

Regarding DEA frontier, the constant returns to scale (CRS) and the variable returns to scale (VRS) output-oriented frontiers are estimated for the same industries. We employed the same output and input variables as the SFA. The technical efficiency scores obtained by using the program DEAP 2.1 are described by Coelli (1996b).

4.2. Comparison of the Efficiency Results

The summary of efficiency results regarding public, private and total are presented in Table 5.

Table 5. Summary Table

		NT*	Minimum	Maximum	Mean	Stnd. Deviation
	SFA	324	0.577	0.984	0.814	0.098
Total	CRS	324	0.786	1.000	0.923	0.037
	VRS	324	0.792	1.000	0.955	0.036
	SFA	162	0.577	0.984	0.791	0.112
Public	CRS	162	0.851	1.000	0.923	0.033
	VRS	162	0.869	1.000	0.957	0.031
	SFA	162	0.673	0.984	0.836	0.075
Private	CRS	162	0.786	1.000	0.923	0.041
	VRS	162	0.792	1.000	0.953	0.040

*number of observation

As can bee seen from the table, the mean technical efficiencies calculated by SFA are less than those of DEA. The studies that compared these two methods obtained mixed results. For example, Sharma *et al.* (1997) found DEA scores to be higher than SFA ones, while Singh *et al.* (2000) obtain higher scores in DEA than SFA, which is similar to our results. The SFA efficiency scores have a higher variability than DEA efficiency scores according to the results of standard deviation. SFA efficiency scores ranges from 0.577 to 0.984, whereas DEA efficiency scores changes from 0.786 to 1.000 and 0.792 to 1.000 regarding CRS and VRS respectively in total. The mean technical efficiency scores of SFA are higher in private sector than the ones in public sector, whilst they are the same in the case of DEA with CRS. Although the efficiency scores do not show substantial difference, the results suggest that public sector has better performance on average regarding DEA with VRS.

Spearman correlation results between SFA efficiency scores and efficiency scores from the DEA are computed and presented in Table 6.

Table 6. Spearman Rank Correlation

	SFA	CRS	VRS
SFA	1.000	0.571**	0.695**
CRS	0.571**	1.000	0.844**
VRS	0.695**	0.844**	1.000

**Correlation is significant at the 1% significance level.

As is clear from the table, all the correlation coefficients are significant, indicating high correlation between the two methods. The weakest correlation coefficient (0.571) is between SFA and DEA with CRS. Although we obtain high correlation of technical efficiency values between the methods and close values on average, we obtained some dissimilarities in terms of ranking of the provinces (see Table 7 and Table 8).

The efficiency scores of both SFA and DEA are reported in Table 7.

Table 7. Technical Efficiency on Average*

	Stoch. Frontier		DEA with CRS		DEA with VRS	
Provinces	Public	Private	Public	Private	Public	Private
Adana	0.789(10)	0.832(7)	0.904(13)	0.927(5)	0.938(11)	0.971(6)
Ankara	0.843(6)	0.874(4)	0.935(7)	0.926(7)	0.969(6)	0.972(5)
Balikesir	0.699(16)	0.796(11)	0.897(14)	0.922(10)	0.919(14)	0.949(14)
Bolu	0.694(17)	0.793(13)	0.879(16)	0.918(12)	0.898(16)	0.950(13)
Bursa	0.845(5)	0.754(18)	0.905(11)	0.927(5)	0.929(13)	0.981(4)
Denizli	0.898(4)	0.776(16)	0.885(15)	0.906(17)	0.951(9)	0.947(15)
Eskisehir	0.745(11)	0.810(9)	0.911(10)	0.917(13)	0.938(11)	0.954(11)
Gaziantep	0.737(13)	0.867(5)	0.949(5)	0.897(18)	0.960(8)	0.938(18)
Icel	0.808(8)	0.817(8)	1.000(1)	0.921(11)	1.000(1)	0.955(10)
Istanbul	0.981(1)	0.983(1)	0.931(8)	0.936(2)	0.969(6)	1.000(1)
Izmir	0.950(2)	0.954(3)	0.959(4)	0.929(3)	0.993(4)	0.982(3)
Kayseri	0.700(15)	0.778(15)	0.873(17)	0.911(15)	0.896(17)	0.953(12)
Kirklareli	0.624(18)	0.801(10)	0.858(18)	0.928(4)	0.866(18)	0.960(9)
Koceli	0.944(3)	0.956(2)	0.990(3)	0.947(1)	1.000(1)	0.991(2)
Konya	0.724(14)	0.759(17)	0.916(9)	0.908(16)	0.944(10)	0.944(16)
Manisa	0.793(9)	0.842(6)	0.904(13)	0.923(9)	0.918(15)	0.963(8)
Tekirdag	0.829(7)	0.796(12)	1.000(1)	0.924(8)	1.000(1)	0.970(7)
Zonguldak	0.742(12)	0.782(14)	0.939(6)	0.914(14)	0.970(5)	0.941(17)

* the rankings of the provinces are shown in parentheses

As can be seen from the table, there are significant differences in efficiency scores (ranging from 0.624 in Kirklareli to 0.981 in Istanbul) in the case of public sector regarding SFA. In the private sector there is a similar pattern and the scores change from 0.754 in Bursa to 0.983 in Istanbul. On the other hand, the variability of efficiency scores is not so great in the case of DEA. The smallest efficiency score (0.858) belongs to Kirklareli, while some provinces such as Icel, Tekirdag, and Istanbul are found to be on the frontier.

Also, one can notice from Table 7 that there are not substantial differences in the ranking of efficiency scores with respect to both CRS and VRS regarding DEA, while it changes drastically as far as SFA is concerned. For example, although Denizli comes in the fourth place in SFA it comes in the fifteenth place in DEA with CRS in the ranking regarding the public sector.

With regard to the private sector, one can say that in spite of these inconsistencies, the ranking of first three provinces, namely, Istanbul, Izmir and Kocaeli does not change. This is not surprising because these three provinces are highly industrialized and constitute approximately 50% of value added in Turkey (see SIS Annual Manufacturing Industry Statistics 1998). Also, the ranking at the bottom of the table is consistent in general (for example Denizli and Konya). This might be due to unplanned investments in these two provinces after 1990. On the other hand, the ranking of Gaziantep changes from the last place in DEA to the fifth place in SFA.

Another point is that the ranking does not change in the first four provinces, namely, Icel, Tekirdag, Kocaeli and Izmir, in the case of DEA (both CRS and VRS) regarding public sector. However, this is not valid as far as SFA is concerned. For example, although Istanbul is ranked as being the first in SFA, it is ranked as being eighth in CRS and sixth in VRS. Also, Icel is in the first place in CRS and VRS, while it is in the eighth place in SFA.

The general good correspondence (correlation and average) between the two sets of efficiency results does suggest that both methods are credible techniques for measuring relative efficiency. However, a detailed analysis suggests that one should be careful to make analysis just relying on only one of these techniques as there are considerable variation across the two measures as far as ranking is concerned. Hence, as other researchers such as Drake (2001) and Singh *et al.*

(2000) point out, it is difficult to get conclusive results by comparing these two techniques.

4.3. Sources of Inefficiency

As Kumbhakar and Bhattacharya (1992), Taymaz and Saatçi (1997), Wadud and White (2000) point out there are various reasons for the efficiency differential. Socio-economic, demographic, regional, environmental and non-physical factors are among them. Some of those reasons incorporate plant-specific and industry-specific factors. Providing a full account of justification of efficiency differential requires the collection of all relevant data and a careful examination of various reasons for each province, for each industry, or even for each plant as case studies. Therefore, we confine ourselves here just to pointing out the effects of average firm size, regional agglomeration, and time trend on technical efficiency.

The results of sources of inefficiency are presented in Table 8[8].

Table 8. Factors Affecting Inefficiency

	SFA	DEA with CRS	DEA with VRS
Constant	0.130	0.097*	0.032*
	(0.730)	(9.019)	(3.338)
ln(averagesize)	0.052*	-0.002	0.004*
	(2.278)	(-1.36)	(2.397)
Region	-5.069*	-0.015*	-0.231*
	(-2.519)	(-4.903)	(-8.514)
Year(time trend)	-0.144	0.012*	0.007
	(-0.866)	(1.859)	(1.239)
R-square		0.086	0.196

*significant at 5% level

As the table shows the sign of average firm size is positive and significant regarding both SFA and DEA with VRS. This indicates that small firm size has a positive effect on technical efficiency. On the other hand the sign of average firm

[8]Regarding DEA we followed a two stage est*imation approach, in which firstly all of the inefficiency scores are found through linear programming and afterwards inefficiency scores from the first stage are regressed upon the variables that affect inefficiency (see Coelli et al., 1998 p 171 for details).*

size regarding DEA with CRS has negative sign but is not significant. In spite of this, SFA and DEA with VRS results suggest that the provinces with smaller average firm sizes have some advantages as far as the efficiency is concerned. With respect to regional agglomeration we obtained negative and significant coefficients in all cases, which means that agglomeration and urbanization economies exist in the manufacturing sector. In contrast to our results, Taymaz and Saatçi (1997) did not found the same relationship. The coefficients of time trend are negative with SFA and positive with DEA with VRS but are insignificant in both cases. The coefficient of DEA with CRS is positive and significant indicating that efficiency decreases as the time changes. Zaim and Taşkın (2001) also conclude that the technical efficiency in the Turkish Manufacturing sector is in a declining trend for time period 1974-1991.

5. Conclusion

This study appears to be the first to employ both DEA and SFA methods to explore technical efficiency in the Turkish manufacturing industry at the regional level. In the study, we also subdivided manufacturing industry into the public and private sector in order to see which one is more efficient at the regional level.

The efficiency measures are estimated under the specifications of Hicks-neutral translog production frontier with inefficiency effects under the stochastic method. The output-oriented frontiers are estimated under the specification of CRS and VRS as far as DEA is concerned. The results revealed that the estimated mean technical efficiency in the DEA is larger than those obtained from SFA analysis. On average, the manufacturing industry could increase efficiency by 5-20%, if they could operate on the efficient frontier. On the other hand, the correlation between efficiency rankings of the two methods is positive and highly significant.

The technical inefficiency effects are examined as a function of average firm size, regional agglomeration, and time. The results from both SFA and DEA methods indicate that small firm size and regional agglomeration have a positive impact on efficiency.

The results of the study also revealed important information concerning the ranking of provinces as far as technical efficiency is concerned. Specifically, the results show that there are substantial differences in ranking of provinces in the two methods. However, the results of both methods show that Istanbul, Kocaeli and Izmir are the most efficient provinces. Regarding technical efficiency, the results from the two methods do not show us consistent results to determine whether the public sector or the private sector is more efficient.

Hence, since it is difficult to produce robust efficiency results in general, one should be cautious when analysing the results by taking only one method into account.

ÖZET

TÜRK İMALAT SANAYİNİN ETKİNLİĞİNİN HESAPLANMASINDA DEA VE SFA YÖNTEMLERİNİN KARŞILAŞTIRILMASI

Bu çalışmanın amacı, 1990-1998 dönemi panel verileri ile Türk imalat sanayiinde seçilmiş illerde teknik etkinlik düzeyini veri zarflama analizi ve stokastik sınır analizi yöntemlerini kullanarak tahminlemek ve bu yolla iki yöntemi karşılaştırmaktır. Bu yöntemlerle elde edilen etkinlik değerlerinin karşılaştırılması sonucunda, iki yöntemin illerin etkinlik sıralamasında önemli derecede farklılık yarattığı; ortalama firma büyüklüğü ve bölgesel yığılmanın etkinlik üzerinde etkide bulunduğu ortaya çıkmıştır.

Anahtar Kelimeler : Teknik etkinlik, stokastik üretim sınırı, veri zarflama analizi, Türk imalat sanayi.

REFERENCES

AIGNER D.J., Lovell CAK and SCHMIDT P. (1977), " Formulation and Estimation of Stochastic Frontier Production Function Models", *Journal of Econometrics* 6: 21-37.

BALCILAR M. and ÇOKGEZEN M. (2001), "Comparative Technical Efficiencies of State and Privately Owned Sugar Plants in Turkey", *Marmara University Discussion Papers* 2001/1.

BATTESE G.E.and COELLI T.J. (1995), "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data", *Empirical Economics*, 20: 325-332.

CHARNES A., COOPER W.W. and RHODES E. (1978), "Measuring the Efficiency of Decision Making Units" *European Journal of Operational Research* 2: 429-444.

CHARNES, A. COOPER, W.W. LEWIN, A.Y. and SEIFORD L.M. (1995), "*Data Envelopment Analysis: Theory, Methodology and Applications"*, Kluwer Academic Publishers, Boston.

COELLI T.J. (1996a), "A Guide to Frontier Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation", *CEPA Working Papers* 96/07, Australia.

COELLI T.J. (1996b), "A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program", *CEPA Working Papers* 96/08, Australia.

COELLI, T.J. RAO D.S.P. and BATTASE G.E. (1998), "*An introduction to efficiency and productivity analysis",* Kluwer Academic Publishers.

CORNWELL, C. SCHMIDT P. and SICKLES R.C. (1990), "Production Frontiers With Cross-Sectional and Time-Series Variation in Efficiency Levels", *Journal of Econometrics* 46: 185-200.

COOPER, W.W. KUMBHAKAR, S. THRALL R.M. and YU X. (1995), "DEA and Stochastic Frontier Analysis of the 1978 Chinese Economic Reforms", *Socio-Economic Planning Sciences* 29: 85-112.

DASHER, K. (2002), "Capital Cities: When do they stop growing?", *Papers in Regional Science* 81: 49-62.

DELİKTAŞ, E. and M. BALCILAR (2002), "A Comparative Analysis of Productivity Growth, Catch-Up and Convergence in Transition Economies, 6th METU International Conference in Economics", September 11-14, Ankara, 2002.

DRAKE, L. (2001), "Efficiency in UK Building Society Branch Networks: A Comparative Analysis Using Parametric and Non-Parametric Distance Functions", *Economic Research Paper* 01/02 Department of Economics, Loughborough University, UK.

DRIFFIELD N. and MUNDAY M. (2001), "Foreign Manufacturing, Regional Agglomeration and Technical Efficiency in UK Industries: A Stochastic Production Frontier Approach", *Regional Studies* 35: 391-399.

FRIED, H.O. LOVELL C.A.K. and SCHMIDT S.S. (1993), "*The Measurement of Productive Efficiency: Techniques and Applications*", Oxford University Press, New York.

GREENE, W.H. (1993), "The Econometric Approach to Efficiency Analysis. In: Fried HO, Lovell CAK, Schmidt SS (eds.)" *The Measurement of Productive Efficiency: Techniques and Applications*. Oxford University Press, New York, 68-119.

KALIRAJAN K.P. and SHAN R.T. (1999), "Frontier Production Functions and Technical Efficiency Measures", *Journal of Economic Surveys* 13: 149-172.

CODE D.A. and PALM F.C. (1986), "Weld Criteria for Jointly Testing Equality and Inequality Restrictions", *Econometrica* 54: 1243-1248.

KRUEGER A.O. and TUNCER B. (1982), "Growth of Factor Productivity in Turkish Manufacturing Industries", *Journal of Development Economics* 11:307-325.

KUMBHAKAR, S.C. (1990), "Production Frontiers, Panel Data and Time-Varying Technical Efficiency", *Journal of Econometrics* 46: 201-211.

KUMBHAKAR S.C. and BHATTACHARYA A. (1992), "Price Distortion and Resource Use Efficiency in Indian Agriculture: A Restricted Profit Function Approach", *Review of Economics and Statistics* 74: 231-239.

MEEUSEN, W. and VAN DEN BROCK J. (1977), "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error", *International Economic Review* 18: 435-444.

MILAN J.A. and ALDAZ N. (2001), "Efficiency and Technical Change in a Panel DEA Framework", *VII European Workshop on Efficiency and Productivity Analysis.*

PITT M.M. and LEE L.F. (1981), "Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry", *Journal of Development Economics* 9: 43-64.

REINHARD, S. LOVELL, C.A.K. and THIJSEN G.J. (2000), "Environmental Efficiency With Multiple Environmentally Detrimental Variables; Estimated With SFA and DEA", *European Journal of Operational Research* 121: 287-303.

ÖNDER A.Ö. and LENGER A. (2000), "Productivity in Turkish Manufacturing Industry: A Comparative Analysis on the Basis of Selected Provinces", *ERC Working Papers in Economics*, 00/12, 1-22.

ÖNDER, A.Ö. DELIKTAŞ E. and LENGER A. (2003), "Efficiency in the Manufacturing Industry of Selected Provinces in Turkey: A Stochastic Frontier Analysis", *Emerging Markets Finance and Trade* 39: 98-113.

SEIFORD, L.M. (1996), "Data Envelopment Analysis: The Evolution of the State of the art (1978-1995)", *Journal of Productivity Analysis* 7: 99-138.

SHARMA, K.R. LEUNG P.S. and ZALESKI H.M. (1997), "Productive Efficiency of the Swine Industry in Hawaii: Stochastic Frontier vs. data Envelopment Analysis", *Journal of Productivity Analysis* 8: 447-459.

SINGH, S., COELLI T. and FLEMING E. (2000), "Performance of Dairy Plants in the Cooperative and Private Sectors in India", *CEPA Working Papers* 2/2000, Australia.

State Institute of Statistics *Annual Manufacturing Industry Statistics* (various issues), Turkish Republic Prime Ministry.

State Planning Organization *Main Economic Indicators* (various issues), Turkish Republic Prime Ministry.

TAYMAZ, E. and SAATÇi G. (1997), "Technical Change and Efficiency in Turkish Manufacturing Industries", *Journal of Productivity Analysis* 8: 461-475.

UYGUR, E. (1990), "*Policy, Productivity, Growth and Employment in Turkey, 1960-1989 and prospects for the 1990s*", ILO, MIES Special Topic Study, Geneva.

WADUD, A. and WHITE B. (2000), "Farm Household Efficiency in Bangladesh: A Comparison of Stochastic Frontier and DEA Methods", *Applied Economics* 32: 1665-1673.

YILDIRIM, E. (1989), "Total Factor Productivity Growth in Turkish Manufacturing Industry Between 1963-1983: An analysis", *METU Studies in Development* 16: 65-69.

ZAİM, O. and TAŞKIN F. (1997), "The Comparative Performance of Public Enterprise Sector in Turkey: a Malmquist Productivity Index Approach", *Journal of Comparative Economics* 25: 129-157.

ZAİM, O. and TAŞKIN F. (2001), "The Relative Efficiency of the Public Manufacturing Industry in Turkey: An Intertemporal Analysis Using Parametric and Nonparametric Production Frontiers", In Celasun M. (ed) *State-Owned Enterprises in the Middle East and North Africa: Privatisation, Performance and Reform*, Rutledge, London, 275-290.