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Are Our Export-Oriented Industries Technically More Efficient?

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This paper makes a comparison of technical efficiency scores between groups of exporting and non-exporting industries. Using data from Census of Manufacturing Industries in Pakistan (2005-06), technical efficiency scores of 102 large scale manufacturing industries are estimated. Stochastic Frontier Analysis as well as Data Envelopment Analysis technique are used to estimate technical efficiency scores. In Stochastic Frontier Analysis Translog and Cobb-Douglass Production Functions are specified, whereas in Data Envelopment Analysis technique, efficiency scores are computed under the assumptions of Constant Returns to Scale as well as Variable Returns to Scale. Industries showing high technical efficiency include Tobacco Products, Refined Petroleum Products, Carpets and Rugs, and Meat and Meat Products. Industries showing low technical efficiency include Refractory Ceramic Products, Electricity Distribution and Control Apparatus, Fish and Fish Products, Basic Precious Metals and Aluminum and its Products. Comparison of mean efficiency scores between exporting and non-exporting industries does not indicate any significant difference between efficiency scores across types of industries.

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1. INTRODUCTION

It is generally believed that export-oriented industries are better able to exploit economies of scale due to widening of markets and their exposure to international competition is a major driving force in their adoption of advanced production and marketing techniques. Opportunity cost of idle capacity for these industries is higher, which induces managers to use inputs up to full capacity. On the other hand non-exporting industries (industries with relatively smaller proportion in national exports) work in relatively more protected environment in the form of tariffs and quotas, have small domestic market to sell their products, and their production and marketing techniques are not well up-to-date. These factors may make export-oriented industries more efficient than import-substitution industries.

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These arguments seem plausible but the superiority of export-oriented industries in terms of technical efficiency is an empirical question. The theory of international trade suggests that international trade is driven by factors like comparative advantage and relative factor endowments and factor intensities *across countries*. On the other hand technical efficiency determines how optimally a producer uses inputs in the production of outputs in a group of producers, usually *within a country*. Therefore the only way to check whether exporting industries in a country are comparatively more efficient than non-exporting industries is to test the hypothesis against real data. Empirical evidence contrary to above hypothesis is not difficult to find [see for example Walujadi (2004)]. In this paper we aim to estimate/compute technical efficiency scores for large-scale manufacturing industries in Pakistan. Once these scores are obtained, statistical techniques can be applied to test the hypothesis that export-oriented industries are technically more efficient.

The objective of this paper is two-fold: First, it aims to provide a comparison between technical efficiency scores between groups of exporting industries and non-exporting industries. Second, it identifies the most efficient and least efficient industries in terms of technical efficiency among all manufacturing industries reported in the Census of Manufacturing Industries in Pakistan. More specifically, we compute the technical efficiency scores for the large scale manufacturing industries in Pakistan and employ statistical techniques to test the hypothesis that export-oriented industries are technically more efficient.[1] In the literature technical efficiency is typically estimated/computed by comparison of input-output combination of a Decision Making Unit (industry in this case) with reference to a production frontier, which can be found through various techniques including Stochastic Production Frontier and Data Envelopment Analysis.

The remainder of this paper is structured as follows: Section 2 presents a theoretical review of efficiency measurement. Recent empirical literature on efficiency of manufacturing firms and industries is reviewed in Section 3. In Section 4 methodology and data are discussed. Empirical results are given in Section 5, and Section 6 concludes the discussion.

2. A THEORETICAL REVIEW OF EFFICIENCY MEASUREMENT

Koopmans (1951, p. 60) defines a producer as technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. In other words, with a given technology a producer is technically efficient if it is not possible to produce more output from the same inputs nor the same output with less of one or more inputs without increasing the amount of other inputs. Debreu (1951) and Farrell (1957) define technical efficiency as one minus the maximum equi-proportionate reduction in all inputs that still allows continued production of given outputs (or alternatively, equi-proportionate expansion in outputs with given inputs). A score of unity would imply that the producer is technically efficient and a score of less than one would indicate the extent of technical inefficiency.

[1]Burki and Khan (2005) and Din, *et al*. (2007) address the issue of technical efficiency but these studies do not test for differences between exporting and non-exporting industries.

Although Koopman's definition is theoretically more stringent, in empirical studies the definition proposed by Debreau and Farrell is more commonly used. The reason is that technical efficiency thus defined can be described in terms of a distance function.[2]

An output distance function is defined as:

$$\text{Do}\ (x,y) = \min\{\gamma : y/\gamma \epsilon\ P(y)\}$$

Where x and y are input and output vectors respectively, and $P(y)$ is the feasible production set. In other words output distance function measures how much outputs can be radially expanded for given level of inputs while still remaining within the feasible production set.

Similarly input distance functions can be defined as follows:

$$\text{Di}\ (y,x) = \max\{\delta : x/\ \delta \epsilon\ L(y)\}$$

Where x and y are again input and output vectors respectively, and $L(y)$ is the input requirement set. This function measures radial contraction in inputs for a given level of output while still remaining within the input requirement set.

Estimation of Technical Efficiencies

The pioneering work for measurement of technical efficiency was done by Farrell (1957).[3] This measurement involves the estimation of a frontier against which the performance of productive units can be compared. Following these early works, many writers tried different techniques to estimate/compute the production frontier and efficiencies. Broadly, these techniques can be divided in two major groups:

- Parametric Techniques, and
- Non-Parametric Techniques

Choice of Techniques

Parametric Techniques are based on econometric regression models. Usually a stochastic production, cost, or profit frontier is used, and efficiencies are estimated with reference to that frontier. Parametric techniques require a functional form, and random disturbances are allowed for in the model. Usual tests of significance can be performed in these models. Non-parametric techniques on the other hand do not require a functional form; do not allow for random factors; and all deviations from the frontier are taken as inefficiencies. Consequently, inefficiencies in non-parametric techniques are expected to be higher than those in parametric techniques. Moreover, tests of significance cannot be performed in non-parametric techniques.

The commonly used parametric efficiency techniques are the stochastic frontier analysis (SFA), the thick frontier approach (TFA), and the distribution-free approach (DFA). Whereas, among non-parametric techniques, data envelopment analysis (DEA)

[2]Distance functions were introduced by Malmquist (1953) and Shephard (1953). For a detail discussion on use of distance function for efficiency measurement, see Shephard (1970), and Russell (1985, 1990). The description given here is adapted from Coelli, *et al.* (2005), pp. 47–49.

[3]Farrell actually proposed measurement of input-oriented technical efficiency (explained below). He also introduced the idea of "allocative efficiency", which involves production decisions given output prices. The "technical efficiency" and "allocative efficiency" combined are termed as "economic efficiency" [Coelli, *et al.* (2005), p. 51].

and free disposable hull (FDH) are more commonly used. Unlike SFA, which can be applied on cross-sectional as well as on panel data, DFA requires panel data for estimation. Since data on manufacturing industries in Pakistan is not a panel dataset, DFA becomes unsuitable. Likewise FDH is quite stringent regarding input substitution. As pointed out by Berger and Humphrey (1997):

> "DEA presumes that linear substitution is possible between observed input combinations on an isoquant (which is generated from the observations in piecewise linear forms). In contrast, FDH presumes that no substitution is possible so the isoquant looks like a step function formed by the intersection of lines drawn from observed (local) Leontief-type input combinations."

Since we are using industry-level data, the assumption of no substitution between inputs would not be quite reasonable. The major issue with Thick Frontier Technique (TFA) is that it does not provide a set of individual efficiency scores, which is, in fact, one of the key objectives of this paper. With these considerations, this study uses two most commonly used techniques, one parametric and one non-parametric technique viz. Stochastic Frontier Analysis (SFA), and Data Envelopment Analysis (DEA). These techniques are explained below, but first we shall briefly review the concepts of Input- and Output-Orientation of technical efficiency measurement.

Output- and Input-Orientations

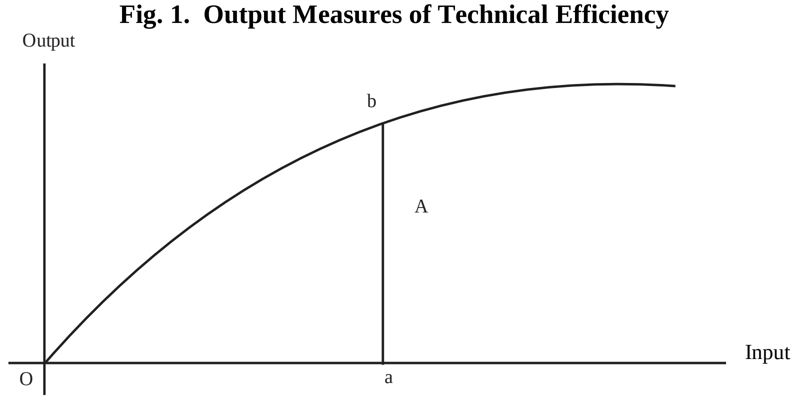
Technical efficiency can be defined either with input-orientation or with an output-orientation. The input-oriented approach defines technical efficiency in terms of proportional reduction in inputs while holding output level constant. The output-oriented approach, on the other hand measures technical efficiency in terms of proportional increase in output while holding input levels constant. This study uses output oriented measure of technical efficiency.

Graphical Representation of Technical Efficiency

Technical efficiency measures how optimally a producer is using inputs in relation to output. In Figure 1 the curve represents the production frontier. For production point A, the output-oriented measure of technical efficiency is given by:

Technical Efficiency = aA/ ab

Fig. 1. Output Measures of Technical Efficiency



This measure of technical efficiency equals the output distance functions [Coelli, *et al*. (2005), pp. 53,56].

Stochastic Frontier Analysis

The SFA is an econometric technique introduced independently by Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977). In this technique the error term of the model is divided into two components, random noise and inefficiency component. Being a parametric technique, SFA requires a functional form, and usual tests of significance can be performed with this technique.

A stochastic production frontier model can be written in general form as:

$$y_i = f(x_i, \beta) + v_i - u_i$$

Where:

y_i is the observed scalar output of the producer i, $i=1,..I$,
x_i is a vector of N inputs used by the producer i,
$f(x_i, \beta)$ is the production frontier,
β is a vector of technology parameters to be estimated.
v_i is the random error, and
u_i is the non-negative random variable associated with technical inefficiency.

In literature different assumptions have been used about distribution of inefficiency term, u_i. Afriat (1972) assumes u_i to have a gamma distribution; Stevenson (1980) uses truncated normal distribution; and Greene (1990) uses two-parameter gamma distribution. Exponential distribution was suggested by Aigner, Lovell, and Schimidt (1977), and Meeusen and Broeck (1977). However, as pointed by Coelli, *et al.* (2005), p. 252, rankings of predicted technical efficiencies are quite often robust to distributional choice. In this study we assume u_i to follow exponential distribution.[4]

The Ordinary Least Square estimation of the above model provides consistent estimates of, slope parameters but not of intercept. More importantly, we cannot obtain efficiency estimates through OLS [Kumbhakar and Lovell (2000), p. 73]. This issue is resolved by applying maximum likelihood estimation technique to obtain consistent parameter estimates as well as efficiency scores. The estimated model forms the basis for computing a predictor of technical efficiencies. The estimates of technical efficiency are obtained as a mean of the conditional distribution of u_i given ε_i, where $\varepsilon_i = v_i - u_i$ [Kumbhakar and Lovell (2000), p. 82].

The next step is to check the significance of inefficiencies estimated by the model, i.e. to test the null hypothesis of no inefficiencies against the alternative hypothesis that inefficiencies are present. As suggested by Coelli (1996), a one-sided likelihood ratio test with a mixed chi-square distribution ($\bar{\chi}^2 = \frac{1}{2}\chi_0^2 + \frac{1}{2}\chi_1^2$) is appropriate here. Therefore, the null hypotheses will be rejected if LR $> \bar{\chi}^2$

Once technical efficiency scores are obtained, we can test whether mean efficiency scores of exporting and non-exporting industries are statistically same or not. We can

[4] Other distributions have also been tried but results from exponential distribution are found to be better in terms of parameter estimates and likelihood ratio test.

divide industries in two groups i.e. exporting and non-exporting industries. Then the following t-test can be applied to test the equality of mean efficiency score of these two groups.

$$t = (\overline{x_1} - \overline{x_2})/\sqrt{[S_p^2/n_1 + S_p^2/n_2]}$$

Where s_p^2 is the pooled variance of two groups, given by the formula:

$$s_p^2 = \{(n_1 - 1)S_1^2 + (n_2 - 2)S_2^2\}/(n_1 + n_2 - 2)$$

$\overline{x_1}$ and $\overline{x_2}$ are average efficiency scores of two groups,

s_1^2 and s_2^2 are variances of average efficiency scores of two groups, and n_1 and n_2 are respective number of industries in two groups.

Data Envelopment Analysis

The Data Envelopment Analysis (DEA) is a mathematical programming technique for the construction of a production frontier. It is an alternative technique for efficiency measurement and possesses certain advantages of its own. It can handle multiple outputs and multiple inputs, and it places no restriction on the functional form of the relationship among inputs and outputs. DEA has some limitations as well. Being a non-parametric technique, DEA is not amenable to direct application of tests of significance and statistical hypothesis testing, and statistical noise is not allowed for.

The DEA models differ in the assumptions that are made about the technology set. The most important assumptions are: free disposability, convexity, returns to scale, and additivity. The free disposability assumption implies that unnecessary inputs and unwanted outputs can be freely discarded. The assumption of convexity assumption implies that any convex combination of feasible production points is feasible as well. The assumption of returns to scale implies possibility of rescaling. The additivity assumption implies that when some production plans are feasible, their sum will also be feasible.[5]

We have applied DEA under two possible returns to scale assumptions: (i) Constant returns to scale, and (ii) Variable returns to scale.

The constant returns to scale model is attributed to Charnes, Cooper, and Rhodes (1978). The model was modified by Banker, Charnes, and Cooper (1984) by imposing an additional convexity constraint to obtain VRS model.

Data Envelopment Analysis can be employed by adopting either of two approaches, viz. output-oriented approach or input-oriented approach. The efficiency scores obtained from these two alternative approaches are identical if constant returns to scales (CRS) are assumed, but are different under the assumption of variable returns to scale (VRS) [Coelli, *et al*. (2005), p. 180]. Moreover, "output- and input-oriented DEA will estimate exactly the same frontier and therefore, by definition, identify the same set of firms as being efficient. It is only the efficiency measures associated with the inefficient firms that may differ between the two methods." [Coelli (2005), p.181].

[5]For details on these assumptions, see Bogetoft and Otto (2010), pp. 85–86.

Fig. 2. Production Frontier under the Assumption of CRS and VRS

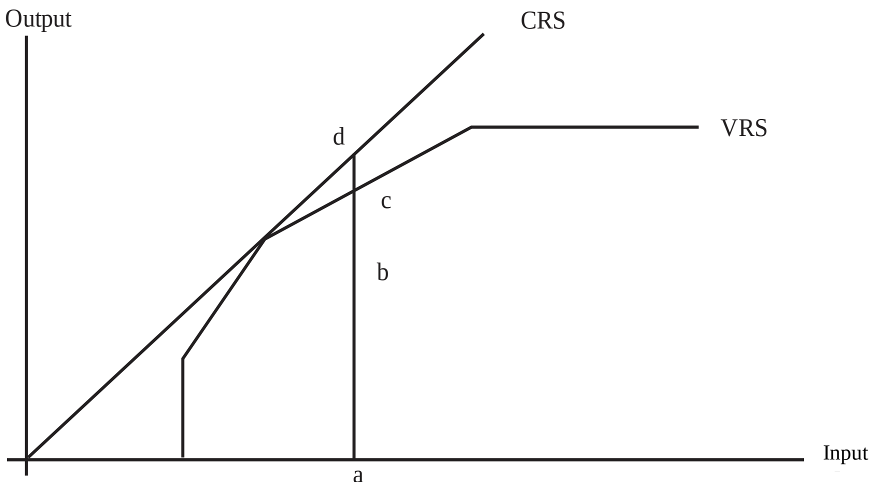


Figure 2 depicts production frontiers under the assumption of CRS and VRS. These are in fact optimal combinations of inputs and outputs. For an industry producing at point b, technical efficiency under CRS will be the ratio ab/ad. Whereas under the assumption of VRS, the technical efficiency measure will be the ratio ab/ac. VRS model gives higher efficiency scores since the frontier fits data more tightly than in the case of CRS.

It is assumed that there are n industries ($j = 1,2,\ldots,n$), each using m different inputs ($h = 1,2,\ldots,m$) and producing a single output. Moreover, it is assumed that $x_{hj} \geq 0$ and $y_j \geq 0$ so that each industry uses at least one positive input and produces positive output. The analysed industry is indicated with subscript *i*. The objective and the constraint of the industry *i* are given by:

$$
\begin{aligned}
& max_{u,v} \;\; uy_i/vx_i \\
& \text{s.t.} \;\; uy_j/vx_j \leq 1 \qquad j = 1,2,\ldots N \\
& u,v \geq 0
\end{aligned}
$$

The vectors u and v represent weights with the restriction that these weights are non-negative. Consequently, neither an output nor an input can be negative. These weights are computed in such away that the efficiency of the analysed industry i is at a maximum and becomes smaller for any other value of u and v. The above objective function is not actually used to compute technical efficiencies. Rather, it is converted into the following linear programming problem:

$$
\begin{aligned}
& min_{u,v} \;\; vx_i \\
& \text{s.t.} \\
& uy_j - vx_j \leq 0 \qquad j=1,2,\ldots n \\
& uy_i = 1 \\
& u,v \geq 0
\end{aligned}
$$

The duality property of linear programming can be used to convert the above problem into the following envelopment form:

$$\begin{aligned}
&Max_{\Phi,\lambda}\ \Phi \\
&\text{s.t.} \\
&-\Phi\ y_i + Y\lambda \geq 0 \\
&x_i - X\lambda \geq 0 \\
&\lambda \geq 0
\end{aligned}$$

Where Φ is a scalar, and λ is a vector of constants. *X* and *Y* represent input and output matrices for all industries. The scalar Φ is the largest factor by which all outputs of industry *i* can be raised. The reciprocal of Φ is the technical efficiency of the *i*th industry. It represents the proportional increase in output that could be achieved by the *i*th industry, with inputs being held constant.

The above programme is for CRS model. For VRS additional convexity constraint (e`λ=1) is imposed in the model. The VRS model is written as:

$$\begin{aligned}
&Max_{\Phi,\lambda}\ \Phi \\
&\text{s.t.} \\
&-\Phi\ y_i + Y\lambda \geq 0 \\
&x_i - X\lambda \geq 0 \\
&\lambda \geq 0 \\
&e`\ \lambda = 1
\end{aligned}$$

Where *e*` is a vector of ones.

The convexity constraint ensures that an inefficient industry is only "benchmarked" against industry of a similar size. That is, the projected point for that industry on the DEA frontier is a convex combination of observed industries [Coelli, (2005), p. 172].

3. A REVIEW OF EMPIRICAL LITERATURE

A detailed review of studies regarding performance of manufacturing sectors in developing countries has been done by Tybout (2000). In the following pages we shall present a brief review of some recent empirical studies, which specifically address the issue of efficiency of manufacturing industries.

Mukherjee and Ray (2004) analyse state level data to study the efficiency dynamics of individual states in India. The study uses data from Annual Survey of Industries for the period 1986-87 to 1999-00. Data Envelopment Analysis technique is used to construct super-efficiency ranking the states in terms of their performance. Stability of efficiency ranking is checked as well as effect of economic reforms introduced in the 1990s. Although considerable variations in efficiency scores are found across the states, no major change is observed in the efficiency ranking of states after the reforms. The study also finds that there is no evidence of convergence in the distribution of efficiency in the post-reform period.

Tripathy (2006) examines efficiency gap between foreign and domestic firms in eleven manufacturing industries of India during 1990-2000. Two different techniques, i.e. SFA and DEA are used to measure efficiency of the firms. The study assumes a Cobb-Douglas technology and estimates stochastic production and cost frontier in each industry to measure technical efficiency and cost efficiency of each firm as well as to obtain some inference on allocative efficiency.

Alvarez and Crespi (2003) explore differences in technical efficiency in Chilean manufacturing firms applying Data Envelopment Analysis technique on plant level. The study uses a sample of 1,091 observations covering all industrial sectors in Chilean Industry according to ISIC three digits. The firms are classified in small, medium and large categories in terms of their annual sales. The efficiency scores indicate that medium firms perform better than the small or large firms. "Professional and scientific equipment" and "Non-metallic mineral products" turn out to be most efficient, whereas, "Agro-industry" and "Textiles" are least efficient. Further, regression analysis is performed to identify some determinants of firms' efficiency. Firms' characteristics like experience are not found to be related with efficiency. On the other hand input quality variables, such as worker experience, product differentiation, and modernisation of capital, are found to positively affect the efficiency of firms.

Ikhsan-Modjo (2006) examines the patterns of total factor productivity growth and technical efficiency changes in Indonesia's manufacturing industries over the period 1988-2000. The study uses the data incorporating both the liberalisation years and the crisis/post crisis years sourced from an annual panel survey of manufacturing establishments. A translog frontier production function is estimated. Gross output is regressed on inputs like the cost of capital, wages, intermediate inputs and energy, and the study finds that technical progress is the most important factor in explaining TFP growth in the Indonesian manufacturing sector.

Kneller and Stevens (2006) investigate whether absorptive capacity helps to explain cross-country differences in the level of technical efficiency. The study uses stochastic frontier technique to estimate a frontier. Industries' output is assumed to depend on four inputs viz. physical capital, effective labour supply (the number of workers adjusted for average hours per week), the stock of human capital and the stock of knowledge. Inefficiency effects are modelled as dependent variable and the independent variables are the level of investment in research and development, level of human capital and country specific dummies. The data consist of a sample of nine manufacturing industries in 12 OECD countries over the period 1973–91. The results indicate differences across countries in efficiencies. It is found that human capital plays a significant and quantitatively important role in explaining these differences.

Din, *et al.* (2007) analyse the efficiency of large scale manufacturing sector in Pakistan using the stochastic frontier as well as data envelopment analysis. The study compares the efficiency scores for the years 1995-96 and 2000-01. The results show that there has been some improvement in the average efficiency of the large scale manufacturing sector from the year 1995-96 to 2000-01. Stochastic frontier technique shows an improvement from 0.58 to 0.65, while for data envelopment analysis the efficiency scores increase from 0.23 to 0.42 (under the assumption of constant returns to scale) and 0.31 to 0.49 (under the assumption of variable returns to scale). However results are mixed at the disaggregated level. Whereas a majority of industrial groups have gained in terms of technical efficiency, some industries have shown deterioration in their efficiency levels including transport equipment, glass and glass products, other non-metallic mineral products, and other manufacturing.

Burki and Khan (2005) analyse the implications of allocative efficiency for resource allocation and energy substitutability. The study covers the period 1969-70 to 1990-91 and utilises pooled time series data from Pakistan's large scale manufacturing sector to estimate a generalised translog cost function. The study also computes factor demand elasticities and elasticities of substitution by using the parameters of the estimated generalised cost function. The results indicate strong evidence of allocative inefficiency leading to over- or under-utilisation of resources and higher cost of production. Input-mix inefficiency takes the form of over-utilisation of raw material and capital *vis-à-vis* labour and energy. The study finds that allocative inefficiency of firms has on average decreased the demand for labour by 0.19 percent and increased the demand for energy by 0.12 percent. Own price elasticities of factors of production imply that the demand for capital is much more sensitive to its own price than the demand for labour. However, the elasticity of substitution between all factors is found out to be positive, which implies that they are substitutes. This is attributed to installation of new but more energy-efficient capital. The new machinery and plants, although more energy-intensive and raw material saving, leave the share of capital and labour unchanged.

Some studies have utilised the Data Envelopment Analysis (DEA) to explore the question of industrial efficiency. Jajri and Rahmah (2006) analyse trend of technical efficiency, technological change and TFP growth in the Malaysian manufacturing sector. The data come from the Industrial Manufacturing Survey of 1984 to 2000 collected by the Department of Statistics, Malaysia. Input variables are capital and labour whereas value added is used as output. It is found that Total Factor Productivity Growth is mainly driven by technical efficiency. The industries that experienced high technical efficiency are food, wood, chemical and iron products. Analysis by industry shows that there is no positive relationship between capital intensity and efficiency, technological change and Total Factor Productivity growth.

Lee and Kim (2006) analyse the effects of research and development (R&D) on Total Factor Productivity growth in manufacturing industries, using a sample of 14 OECD countries[6] for the years 1982-1993. With the assumption of constant returns to scale technology, the Malmquist Productivity Index and its components are computed using two traditional inputs i.e. labour and capital; then the exercise is repeated with the stock of R & D capital as an additional input. Inclusion of R & D capital is found to be statistically significant and the introduction of R & D capital as an additional input reduces the TFP measures on average by 10 percent. This is attributed to "costly" R & D capital formation as opposed to "costless" productivity growth when only labour and fixed capital are considered. It is also found that it is technological progress rather than efficiency catch up that is driven by the accumulation of R & D capital. Spillovers of R & D capital are tested using regression analysis. Two types of spillovers are considered viz. domestic R & D spillovers across industries and international spillovers within a single industry. Domestic R & D capital stocks and foreign R & D capital stocks for different industries are used for this purpose. It is found that productivity gains in manufacturing industries depend significantly on R & D spillovers, especially for an economy that is more open to international trade.

[6]The sample consists of Canada, Denmark, Finland, France, Germany, Italy, Japan, Korea, Netherlands, Norway, Spain, United Kingdom, and United States.

4. METHODOLOGY AND DATA

This study uses both SFA and DEA techniques to measure technical efficiencies. For stochastic frontier two functional forms are tried viz. Translog and Cobb-Douglass production functions. The purpose is to check the sensitivity of the efficiency scores with reference to the functional form/estimation technique.

Model 1

The Stochastic Production Frontier of Translog form is given below:

$$Ln\ Y_i = \beta_0 + \beta_1\ ln\ L_i + \beta_2\ lnK_i + \beta_3\ ln\ RM_i + \beta_4\ ln\ Ener_i + \beta_5\ ln\ NIC_i + \tfrac{1}{2}\beta_6\ (ln\ L_i)^2 + \tfrac{1}{2}\beta_7\ (lnK_i)^2 + \tfrac{1}{2}\beta_8\ (ln\ RM_i)^2 + \tfrac{1}{2}\beta_9\ (ln\ Ener_i)^2 + \tfrac{1}{2}\beta_{10}\ (ln\ NIC_i)^2 + \beta_{11}\ ln\ L_i\ lnK_i + \beta_{12}\ ln\ L_i\ ln\ RM_i + \beta_{13}\ ln\ L_i\ ln\ Ener_i + \beta_{14}\ ln\ L\ ln\ NIC_i + \beta_{15}\ lnK_i\ ln\ RM_i + \beta_{16}\ lnK_i\ ln\ Ener_i + \beta_{17}\ lnK_i\ ln\ NIC_i + \beta_{18}\ ln\ RM_i\ ln\ Ener_i + \beta_{19}\ ln\ RM_i\ ln\ NIC_i + \beta_{20}\ ln\ Ener_i\ ln\ NIC_i + v_i - u_i$$

Where:

Y_i is the value of output,
L_i is the average number of persons engaged,
K_i is the amount of capital used
RM_i is the value of raw material used,
$Ener_i$ is the value of energy consumed,
NIC_i is the non-industrial cost,
v_i and u_i are two components of the error term with following distributional assumptions [Kumbhakar and Lovell (2000), p.80].

(i) $v_i \sim iidN(0, \sigma_v^2)$
(ii) $u_i \sim iid$ with exponential distribution
(iii) u_i and v_i are distributed independently of each other, and of the regressors.

The symmetric error term v_i is the usual noise component to allow for random factors like measurement errors, weather, strikes etc. The non-negative error term $u_i$is the technical inefficiency component. Subscript *i* stands for *i*th industry.

Model 2

The Cobb-Douglass function has the following form:

$$Ln\ Y_i = \alpha_0 + \alpha_1\ ln\ L_i + \alpha_2\ lnK_i + \alpha_3\ ln\ RM_i + \alpha_4\ ln\ Ener_i + \alpha_5\ ln\ NIC_i + v_i - u_i$$

The variables names and distributional assumptions of the composite random term are the same as in the case of the translog function.

The data are obtained from the Census of Manufacturing Industries (2005-06),[7] *In* all, 102 large-scale manufacturing industries are selected.

The following is a brief description of the variables:

[7]This is the latest available published CMI.

Output

CMI reports value added as well as contribution to GDP. Value added reported in CMI does not allow for non-industrial costs. So we have used contribution to GDP as output which equals value of production minus industrial cost minus net non-industrial cost.

Capital

Capital consists of land and building, plant and machinery and other fixed assets, which are expected to have a productive life of more than one year and are in use by the establishment for the manufacturing activity.

Labour

Labour includes employees, working proprietors, unpaid family workers and home workers. Labour data have been adjusted to allow for number of shifts as reported in CMI.

Raw Materials

As defined in CMI (2005-06) "Raw-materials include raw and semi-finished materials, assembling parts etc., which are physically incorporated in the products and by-products made. Chemicals, lubricants and packing materials, which are consumed in the production and spare parts charged to current operating expenses are included. Raw-materials given to other establishment for manufacturing goods (semi-finished and finished) on behalf of the establishment are included, whereas raw material supplied by others for manufacturing goods is excluded."

Energy

This input is obtained by adding cost on fuel and cost on electricity. Fuel is defined as "firewood, coal, charcoal, kerosene oil, petrol, diesel, gas and other such items which are consumed in generating heat and power."

Non-industrial Costs

These consist of payments for transport, insurances, copy rights/royalties, postage, telephone, fax and internet charges, printing and stationery, legal and professional services, advertising and selling services, traveling, etc.

Exporting and Non-exporting Industries

The distinction between exporting and non-exporting industries is made on the basis of shares of industries in total exports for the year 2005-06. The CMI data are based on ISIC classification. Data on exports could not be obtained in this classification. Exports Receipts, June 2006,[8] published by State Bank of Pakistan are used to identify exporting industries. These industries are manually matched with ISIC classification. List of all industries covered in this study is given in Appendix with top twenty exporting

[8]Now this publication is named as "Export of Goods and Services".

industries marked with "Ex". These twenty industries constitute the group of "exporting industries". Remaining industries are treated as "non-exporting industries". "Exporting industries" cover more than 88 percent of total exports.

Main focus of this paper is to determine whether major exporting manufacturing industries are technically more efficient than other industries. For this purpose industries are divided in two groups. Twenty exporting industries constitute group 1, and remaining industries constitute group 2. Separate mean efficiency scores and standard deviations of technical efficiency scores are computed for these groups of industries. Finally, t-test outlined in Section 2 is used to check the following null hypotheses:

$$MTE_1^{Trans} = MTE_2^{Trans}$$
$$MTE_1^{CD} = MTE_2^{CD}$$
$$MTE_1^{DEACR} = MTE_2^{DEACR}$$
$$MTE_1^{DEAVR} = MTE_2^{DEAVR}$$

Where *MTE* stands for mean technical efficiency score. Subscripts 1 and 2 denote two groups, and superscripts Trans, CD, DEACR and DEAVR indicate the techniques used i.e. Stochastic Frontier Translog, Stochastic Frontier Cobb-Douglass, Data Envelopment Analysis under constant returns to scale, and Data Envelopment Analysis under variable returns to scale respectively. The above four hypotheses are tested against the alternative hypotheses that mean efficiency scores are not equal, i.e. two-tail tests will be used to test the hypotheses.

Two different computer packages are used to obtain efficiency scores. For SF model the computer package STATA 9[9] is used, and for DEA model Win4DEAP[10] (Version 1.1.2) is used. Identification of output and inputs is same in both techniques.

5. RESULTS

Results of regression equation for SF are given in Tables 1 and 2. The results for Translog specification show that Raw Material and Non-Industrial Costs are highly significant in explaining output. Non-Industrial Costs variable is significant at almost 100 percent level, whereas significance of Raw Material is about 98 percent. Labour and Capital are significant at about 92 percent level. Significance of Energy is rather low, but it is still a relevant variable. Sign of capital turns out to be negative whereas square term of capital has a positive sign. This might be an indication of threshold point beyond which capital starts contributing positively to the output. Signs of product terms indicate complementarity among inputs. The variances of two error terms v_i and u_i are denoted by σ_v^2 and σ_u^2 respectively. In the log likelihood, they are parameterised as $\ln \sigma_v^2$ and $\ln \sigma_u^2$ respectively. The estimate of the total error variance which is sum of these two variances is denoted by σ^2 (i.e. $\sigma^2 = \sigma_v^2 + \sigma_u^2$). The parameter λ stands for the ratio of the

[9]STATA programme is a general-purpose statistical software package, developed by STATA Corp.

[10]Win4DEAP is a free software developed by Michel Deslierres. (Département d'économie Université de Moncton). It is available at http:/www.umoncton.ca/desliem/dea. This package is an extension of the computer programme DEAP, developed by Professor T. Coelli (for detail see "A guide to DEAP version 2.1: A Data Analysis Computer Programme." CEPA Working Paper 96/08).

variance of these two error terms (i.e. $\lambda = \sigma_u / \sigma_v$). These two parameterisations indicate relative importance of the two components of error term.

Mean Efficiency score is 0.7401 with standard deviation of 0.1346. Likelihood-ratio test indicates that the use of stochastic frontier approach is justified. The results of a likelihood-ratio test are reported at the bottom of the above Table. Here the null hypothesis is that there is no technical inefficiency component in the model, i.e.

$H_0: \sigma_u = 0$

Against the alternative hypothesis

$H_1: \sigma_u > 0$

The acceptance of null hypothesis would have implied that the stochastic frontier model reduces to an OLS model with normal errors. However in our case evidence is strong enough to reject the null hypothesis. The hypothesis of no technical inefficiency component in the model is rejected at less than 0.01 level of significance.

Table 1

Translog Production Frontier Results
(for Overall Dataset Covering 102 Industries)

	Coeff	z	P>z		Coeff	z	P>z
Constant	4.75	1.47	0.141	L*K	–0.11	–1.28	0.202
L	2.54	2.95	0.003	L*RM	–0.11	–0.85	0.395
K	–2.71	–3.09	0.002	L*Ener	–0.03	–0.24	0.809
RM	0.71	1.41	0.159	L*NIC	–0.12	–0.95	0.344
Ener	0.80	1.63	0.104	K*RM	0.04	0.41	0.681
NIC	.41	0.57	0.567	K*Ener	–0.22	–2.12	0.034
L^2	0.18	2.29	0.022	K*NIC	0.13	1.15	0.249
K^2	0.14	1.97	0.049	RM*Ener	–0.01	–0.08	0.938
RM^2	0.16	2.89	0.004	RM*NIC	–.36	–2.57	0.010
$Ener^2$	0.16	2.36	0.018	Ener*NIC	–.10	–1.05	0.296
NIC^2	0.21	2.63	0.009				
$\ln \sigma_v^2$	–1.99	–8.32	0.000				
$\ln \sigma_u^2$	–2.22	–5.07	0.000				
σ_v	0.37	.0442					
σ_u	0.33	.0721					
σ^2	0.24	.0421					
λ	0.89	.1018					

Likelihood-ratio test of $\sigma_u = 0$

$\bar{\chi}^2 = 7.34$

Prob $\geq \bar{\chi}^2 = 0.003$

Mean Efficiency score = 0.7401
SD of Efficiency scores = 0.1346.

In Cobb-Douglass specification (Table 2), all inputs are highly significant except $Ener_i$. Mean Efficiency score is 0.7412 with standard deviation of 0.1014. Again, the hypothesis of no technical inefficiency component in the model is rejected, however at a lesser level of significance than that of translog model. Here level of significance is about 0.06 for rejection of null hypothesis of no technical inefficiencies. Mean of efficiency scores and their standard deviation are found to be very close to those of translog model.

Table 2

Cobb-Douglass Production Frontier Results
(for Overall Dataset Covering 102 Industries)

Independent Variables	Coefficients	z	P>z
Constant	2.51	4.63	0.00
L_i	0.15	1.73	0.08
K_i	0.16	1.76	0.08
RM_i	0.17	2.34	0.02
$Ener_i$	0.08	1.37	0.17
NIC_i	0.40	4.47	0.00
$\ln \sigma_v^2$	–1.14	–5.56	0.00
$\ln \sigma_u^2$	–2.31	–3.58	0.00
σ_v	0.57		
σ_u	0.31		
σ^2	0.42		
λ	0.56		

Likelihood-ratio test of $\sigma_u = 0$
$\bar{\chi}^2 = 2.31$
Prob $\geq \bar{\chi}^2 = 0.064$
Mean Efficiency score = 0.7412
SD of Efficiency scores = 0.1014.

Efficiency scores obtained from SF models are reported in Appendix (along with those of DEA model). In Cobb-Douglass as well as translog models of stochastic frontier, average efficiency is found to be about 0.74 with standard deviations of 0.13 and 0.10 respectively. This shows that efficiency scores of most of the industries cluster around the mean value in a very narrow band with a very small number of observations going to either extremes (Figures 4 and 5).

Fig. 4. Efficiency Scores from Translog Frontier

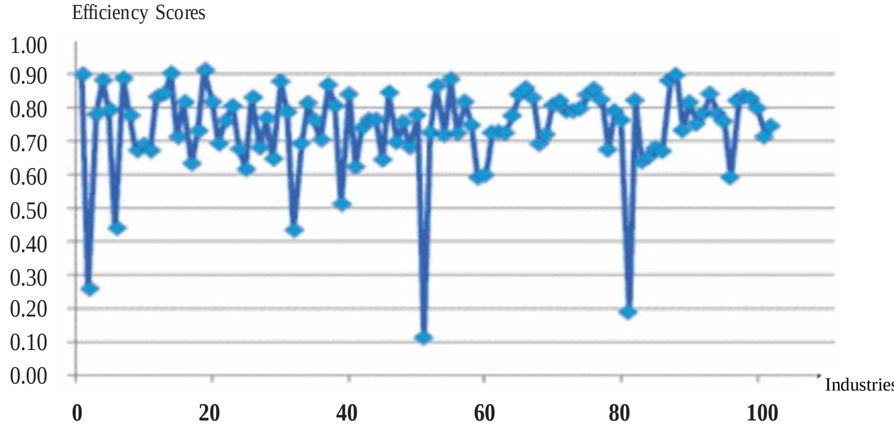
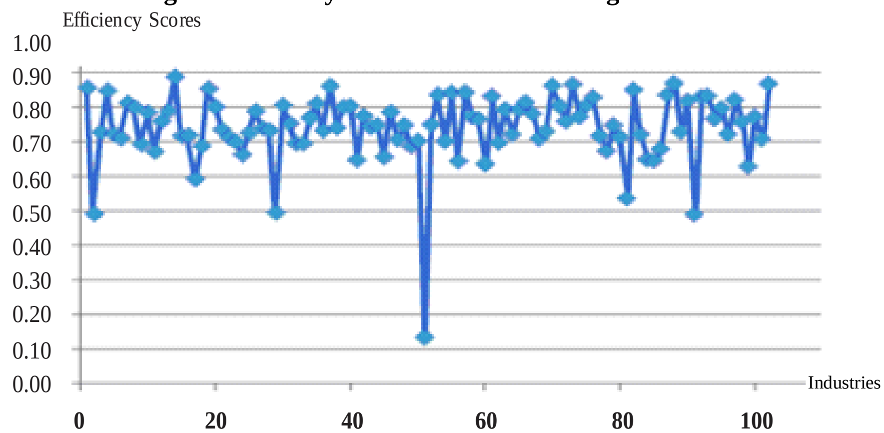


Fig. 5. Efficiency Scores from Cobb-Douglas Frontier



Efficiency scores of most efficient industries are reported in Table 3. As the scores indicate, most of the industries efficient in Translog Model are also efficient in Cobb-Douglass Model. These are Carpets and Rugs, Tobacco Products, Meat and Meat Products, Sound/video Apparatus of TV and Radio and Vegetable and Animal Oils and Fats, and Refined Petroleum Products.

Table 3

Most Efficient Industries (by SF Model)

Translog Frontier	Efficiency Scores	Cobb-Douglass Frontier	Efficiency Scores
Carpets and Rugs	0.91	Tobacco Products	0.89
Tobacco Products	0.90	Sound/video Apparatus of TV and Radio	0.87
Meat and Meat Products	0.90	Recycling	0.87
Sound/Video Apparatus of TV and Radio	0.90	Manufacture of Machine Tools	0.87
Starches and Starch Products	0.89	Ovens, Furnaces and Furnace Burners	0.86
Cutting, Shaping and Finishing of Stone	0.89	Refined Petroleum Products	0.86
Vegetable and Animal Oils and Fats	0.88	Meat and Meat Products	0.86
TV, Radio and Telegraphy Apparatus	0.88	Carpets and Rugs	0.85
Pulp, Paper and Paperboard	0.88	Insulated Wire and Cables	0.85
Refined Petroleum Products	0.87	Vegetable and Animal Oils and Fats	0.85

Efficiency scores of least efficient industries are reported in Table 4. Refractory Ceramic Products happens to be the least efficient industry by a wide margin in both models; its efficiency score being only 0.11. This indicates a very non-optimal utilisation of inputs. Next in the list are Electricity Distri. and Control Apparatus, Fish and Fish Products, and Basic Precious Metals and Aluminum and its Products; all these industries are relatively less efficient according to the both models.

Table 4

Least Efficient Industries (by SF Model)

Translog Frontier		Cobb-Douglass Frontier	
Industries	Efficiency Scores	Industries	Efficiency Scores
Refractory Ceramic Products	0.11	Refractory Ceramic Products	0.13
Electricity Distri. and Control Apparatus	0.19	Watches and Clocks	0.49
Fish and Fish Products	0.26	Fish and Fish Products	0.49
Other Articles of Paper and Paperboard	0.43	Other Products of Wood	0.49
Grain Mill Products	0.44	Electricity Distri. and Control Apparatus	0.54
Fertilisers and Nitrogen Compounds	0.51	Finishing of Textiles	0.59
Other First Processed Iron and Steel	0.59	Musical Instruments	0.63
Motorcycles	0.59	Basic Precious Metals and Aluminum and its Products	0.64
Basic Precious Metals and Aluminum and its Products	0.60	Other Non-Metallic Mineral Products	0.64
Luggage, Saddlery and Harness	0.62	Other Electrical Equipment n.e.c.	0.65

DEA model has been applied under two assumptions; (i) Constant returns to scale, and (ii) Variable returns to scale. Mean efficiency in DEA models turns out to be 0.43 and 0.51 with standard deviations of 0.27 and 0.29 respectively under these two assumptions. These scores are slightly less than that of SF models due to different assumptions regarding the inefficiency term. Industry-wise technical efficiency scores are given in Appendix. Like the SF case, we observe the pattern of clustering of efficiency score in a narrow band around the mean value in DEA models as well (Figures 6 and 7).

Fig. 6. Efficiency Scores from DEA (Constant Returns to Scale)

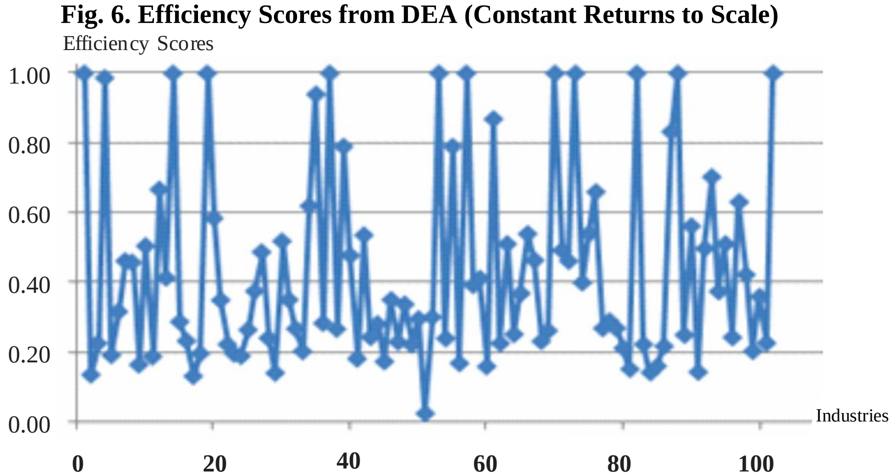
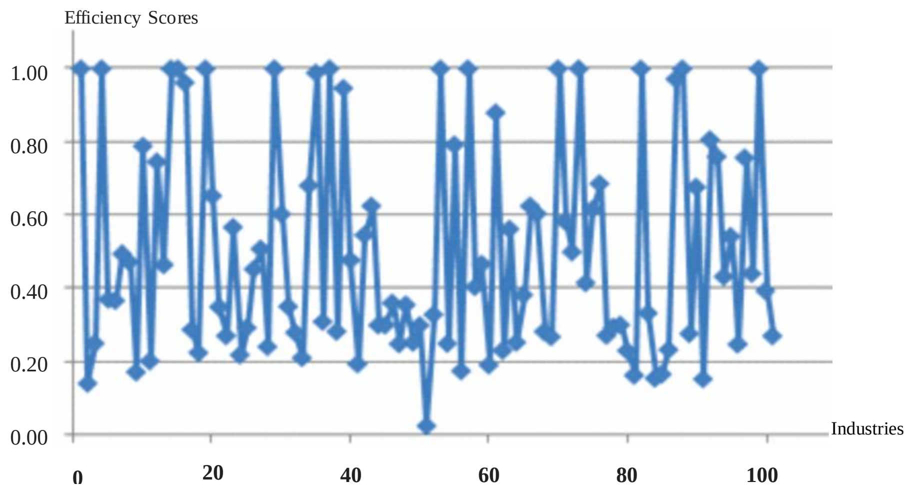


Fig. 7. Efficiency Scores from DEA (Variable Returns to Scale)



Ten most efficient industries in DEA models under assumption of constant returns to scale and variable returns to scale are reported in Table 5. Since DEA model does not allow for random error, the most efficient industries are likely to lie exactly on the frontier. All such industries reported in Table 5 have efficiency score of 1. Meat and Meat Products, Tobacco Products, Carpets and Rugs, Refined Petroleum Products, Cement, Lime and Plaster, Basic Iron and Steel, Ovens, Furnaces and Furnace Burners, are the sectors with relatively high efficiency scores under both the assumptions of DEA model. It should be noted that Meat and Meat Products, Tobacco Products, Carpets and Rugs, and Refined Petroleum products are efficient industries common in all models.

Table 5

Most Efficient Industries by DEA Model

Constant Returns to Scale	Variable Returns to Scale
Meat and Meat Products	Meat and Meat Products
Tobacco Products	Vegetable and Animal Oils and Fats
Carpets and Rugs	Tobacco Products
Refined Petroleum Products	Spinning of Textiles
Cement, Lime and Plaster	Carpets and Rugs
Basic Iron and Steel	Other Products of Wood
Ovens, Furnaces and Furnace Burners	Refined Petroleum Products
Manufacture of Machine Tools	Cement, Lime and Plaster
Insulated Wire and Cables	Basic iron and Steel
Sound/Video Apparatus of TV and Radio	Ovens, Furnaces and Furnace Burners

Least efficient industries under DEA model under the assumptions of Constant Returns to Scale and Variable Returns to Scale are given in Table 6. Again, Refractory Ceramic Products turned out to be least efficient industry with a very small score of 0.03. Fish and Fish Products, Electric Lamps and Lighting Equipment, Electricity Distribution

Table 6

Least Efficient Industries by DEA Model

Constant Returns to Scale		Variable Returns to Scale	
Industries	Efficiency Scores	Industries	Efficiency Scores
Refractory Ceramic Products	0.03	Refractory Ceramic Products	0.03
Finishing of Textiles	0.13	Fish and Fish Products	0.14
Fish and Fish Products	0.14	Watches and Clocks	0.15
Other Products of Wood	0.14	Electric Lamps and Lighting Equipment	0.16
Electric Lamps and Lighting Equipment	0.14	Electricity Distri. and Control Apparatus	0.16
Watches and Clocks	0.14	Other Electrical Equipment n.e.c.	0.17
Electricity Distri. and Control Apparatus	0.15	Bakery Products	0.17
Basic Precious Metals Aluminum and its Products	0.16	Other Non-Metallic Mineral Products	0.18
Other Electrical Equipment n.e.c.	0.16	Basic Precious Metals Aluminum and its Products	0.19
Bakery Products	0.17	Pesticides and Agrochemical Products	0.19

and Control Apparatus, Basic Precious Metals and Aluminum and its Products are relatively less efficient industries under both the assumptions of scale. Refractory Ceramic Products, Fish and Fish products, Electricity Distribution and Control Apparatus, and Basic Precious Metals and Aluminum and its products are relatively less efficient in all the four models.

In general the efficiency scores computed through SFA turn out to be higher than those computed through DEA. This is due to the fact that SFA allows for random noise while estimating the frontier. Within DEA technique efficiency scores under CRS are, generally, lower than those under VRS. This occurs because under VRS assumption the frontier encloses the observations in a more compact way. So, observations become closer to the frontier. As pointed out by Din, *et al.* (2007), this is in line with the evidence suggested in the literature, e.g. Lin and Tseng (2005). This consistency of efficiency rankings again confirms that results are not sensitive to the technique employed. A direct comparison of theses individual efficiency scores with previous studies is not possible. As mentioned before Burki and Khan (2005) do not provide individual efficiency scores. Din, *et al.* (2007) do provide individual efficiency scores but they use a different industrial classification and aggregation level. So their efficiency scores are not directly comparable with the present study.

Next, we turn to the efficiency of exporting industries. Mean efficiency scores of exporting industries are compared with those of non-exporting industries by using t-test. The results of these tests are summarised in Table 7.

Table 7

Comparison of Mean Efficiency Scores between Exporting and Non-Exporting Industries

Technique	*t*-Values
Stochastic Frontier (CD)	–0.49
Stochastic Frontier (Translog)	–0.57
DEA (CRS)	–1.05
DEA (VRS)	–0.14

As the t-values suggest, there is no significant difference between mean efficiency scores of exporting and non-exporting industries. Therefore we do not reject the null hypotheses of equality of mean efficiency scores across exporting and non-exporting industries. In other words exporting industries are not performing better than non-exporting industries in terms of technical efficiency in a significant way. Rather, as the Table shows, mean efficiency score in all the four models is slightly *less* for exporting industries (though not in a significant way). This is against the common perception that exporting industries must be the most efficient ones. This may be an indication of inherent comparative advantage of exporting industries rather than more efficient performance as the main factor for exports. On the other hand it also indicates a significant margin for improvement in export performance if only technical efficiency of manufacturing industries could be improved through better use of given inputs.

Limitations of the Paper

The paper uses data of 102 industries groups defined at 4-digits level of aggregation. At this level of aggregation, many diversified industries are lumped within a broader industrial group, thus masking important characteristics specific to an industry. Benefits of broader analysis notwithstanding, an analysis based upon a more disaggregated dataset could bring these differences into focus. The second limitation is about the methodology. The estimated models provide technical efficiency scores, but do not go beyond any further. There remain unanswered questions about causes of differences in efficiency scores among different industrial groups. Many factors like protection, concentration, human resource development, institutional strengthening etc. are responsible for differences in technical efficiencies. Empirical testing is needed to determine direction and size of their respective effects. These limitations indicate potential for future work in this area.

6. SUMMARY AND CONCLUSIONS

In this paper technical efficiency levels of manufacturing industries are estimated by using SFA and DEA techniques. SFA technique is used to estimate Cobb-Douglass as well as translog production frontier. DEA technique is used under the assumptions of constant returns to scale and variable returns to scale. The results suggest that the overall efficiency of manufacturing industries is low and there is a substantial room for improvement. Industries showing high technical efficiency include Tobacco Products, Refined Petroleum Products, Carpets and Rugs, and Meat and Meat Products. Industries showing low technical efficiency include Refractory Ceramic Products, Electricity Distribution and Control Apparatus, Fish and Fish Products, Basic Precious Metals and Aluminum and its Products.

Efficiency scores of exporting industries are statistically not better than other industries. This indicates that there is a scope for improving technical efficiency to gain a competitive edge in export markets.

APPENDIX

Efficiency Scores of Industries

			Technical Efficiency Scores			
	Industry		SFA	SFA	DEA	
S. No.	Codes	Industries	Cobb	Trans	CRS	VRS
1	1511	Meat and meat products	0.86	0.90	1.00	1.00
2	1512	Fish and fish products (Ex)*	0.49	0.26	0.14	0.14
3	1513	Fruits, vegetables and edible nuts	0.73	0.78	0.23	0.25
4	1514	Vegetable and animal oils and fats	0.85	0.88	0.99	1.00
5	1520	Dairy products	0.72	0.79	0.19	0.37
6	1531	Grain mill products (Ex)	0.71	0.44	0.32	0.37
7	1532	Starches and starch products (Ex)	0.81	0.89	0.46	0.50
8	1533	Animal feeds (Ex)	0.80	0.78	0.46	0.47
9	1541	Bakery products	0.69	0.67	0.17	0.17
10	1542	Sugar	0.79	0.69	0.51	0.79
11	1543	Cocoa, chocolate and sugar confectionery	0.67	0.67	0.19	0.20
12	1549	Other farinaceous products n.e.c.	0.76	0.83	0.67	0.75
13	1551 &	Spirits; ethyl alcohol	0.79	0.84	0.41	0.47
	1553 &	Malt liquors and malt				
	1554	Soft drinks; mineral water				
14	16	Tobacco products	0.89	0.90	1.00	1.00
15	1711	Spinning of textiles (Ex)	0.72	0.71	0.29	1.00
16	1712	Textile fabrics (Ex)	0.72	0.82	0.23	0.96
17	1713	Finishing of textiles (Ex)	0.59	0.63	0.13	0.29
18	1721	Made-up textile articles, not apparel (Ex)	0.69	0.73	0.20	0.23
19	1722	Carpets and rugs (Ex)	0.85	0.91	1.00	1.00
20	1723	Cordage, rope, twine and netting (Ex)	0.80	0.82	0.59	0.65
21	1729	Other textiles n.e.c. (Ex)	0.74	0.69	0.35	0.35
22	1730	Knitted and crocheted fabrics	0.71	0.76	0.22	0.27
23	1810 &	Wearing apparel, except fur apparel	0.70	0.80	0.20	0.57
	1820	Articles of fur (Ex)				
24	1911	Tanning and dressing of leather (Ex)	0.66	0.68	0.19	0.22
25	1912	Luggage, saddlery and harness (Ex)	0.73	0.62	0.27	0.29
26	1920	Footwear (Ex)	0.79	0.83	0.38	0.45
27	2010	Sawmilling and planking of wood	0.74	0.68	0.49	0.51
28	2021	Plywood, panels and boards	0.73	0.77	0.24	0.24
29	2023 &	Wooden containers	0.49	0.65	0.14	1.00
	2029	Other products of wood				
30	2101	Pulp, paper and paperboard	0.81	0.88	0.52	0.60
31	2102	Containers of paper and paperboard	0.75	0.79	0.35	0.35
32	2109	Other articles of paper and paperboard	0.70	0.43	0.27	0.28
33	2211 &	Printing and publication of books etc.	0.70	0.69	0.20	0.21
	2212	Publishing of newspapers and journals				
34	2213 &	Publishing of music	0.77	0.81	0.62	0.68
	2219	Other publishing				

Continued—

Appendix—(*Continued*)

35	2221	Printing	0.81	0.76	0.94	0.99
36	2222	Service activities of printing	0.73	0.70	0.28	0.31
37	232	Refined petroleum products (Ex)	0.86	0.87	1.00	1.00
38	2411	Basic chemicals	0.74	0.81	0.27	0.28
39	2412	Fertilisers and Nitrogen compounds	0.80	0.51	0.79	0.95
40	2413	Plastics and synthetic rubber (Ex)	0.80	0.84	0.48	0.48
41	2421	Pesticides and agrochemical products	0.65	0.62	0.18	0.19
42	2422	Paints, varnishes, printing ink	0.78	0.74	0.54	0.55
43	2423	Pharmaceuticals	0.74	0.76	0.24	0.63
44	2424	Soaps and detergents	0.75	0.76	0.28	0.30
45	2429 &	Other chemical products	0.66	0.64	0.17	0.30
	2430	Man-made fibres (Ex)				
46	2511	Rubber tyres and tubes; retreading	0.79	0.84	0.35	0.36
47	2519	Other rubber products	0.71	0.70	0.23	0.25
48	2520	Plastic products	0.75	0.76	0.34	0.36
49	2610	Glass and glass products	0.69	0.68	0.22	0.25
50	2691	Non-refractory ceramic ware	0.70	0.78	0.30	0.30
51	2692	Refractory ceramic products	0.13	0.11	0.03	0.03
52	2693	Structural clay and ceramic products	0.75	0.73	0.30	0.33
53	2694	Cement, lime and plaster	0.84	0.86	1.00	1.00
54	2695	Articles of concrete, cement and plaster	0.70	0.72	0.24	0.25
55	2696	Cutting, shaping and finishing of stone	0.84	0.89	0.79	0.79
56	2699	Other non-metallic mineral products	0.64	0.72	0.17	0.18
57	2711	Basic iron and steel	0.84	0.82	1.00	1.00
58	2712	Tubes and tube fittings	0.77	0.75	0.39	0.41
59	2713	Other first processed iron and steel	0.77	0.59	0.41	0.47
60	2721 &	Basic precious metals	0.64	0.60	0.16	0.19
	2722	Aluminium and its products				
61	2724	Copper products	0.83	0.73	0.87	0.88
62	2731	Casting of iron and steel	0.70	0.73	0.23	0.23
63	2811	Structural metal products	0.79	0.72	0.51	0.56
64	2812	Tanks and containers	0.72	0.78	0.25	0.25
65	2892 &	Treating and coating of metals	0.79	0.84	0.37	0.38
	2893	Cutlery and general hardware				
66	2899	Other fabricated metal products n.e.c	0.81	0.86	0.54	0.63
67	2911	Engines and turbines	0.78	0.83	0.46	0.60
68	2912	Pumps, compressors, taps and valves	0.71	0.69	0.23	0.28
69	2913	Driving elements	0.73	0.72	0.26	0.27
70	2914	Ovens, furnaces and furnace burners	0.86	0.81	1.00	1.00
71	2915 &	Lifting and handling equipment	0.80	0.82	0.49	0.58
	2919	Other general-purpose machinery				
72	2921	Agricultural and forestry machinery	0.76	0.79	0.46	0.50
73	2922	Manufacture of machine tools	0.87	0.79	1.00	1.00
74	2923 &	Machinery for metallurgy	0.77	0.80	0.40	0.42
	2924	Mining and quarrying machinery				
75	2925	Machinery for food and tobacco processing	0.81	0.84	0.54	0.62
76	2926	Textile and leather production machinery	0.83	0.86	0.66	0.69
77	2927	Weapons and ammunition	0.72	0.82	0.27	0.27
78	2929	Other special-purpose machinery	0.67	0.67	0.29	0.30
79	2930	Electric domestic appliances	0.75	0.79	0.27	0.30
80	3110	DC motors, generators and transformers	0.71	0.76	0.21	0.23
81	3120	Electricity distri. and control apparatus	0.54	0.19	0.15	0.16
82	3130	Insulated wire and cables	0.85	0.82	1.00	1.00
83	3140	Accumulators, cells and batteries	0.72	0.64	0.22	0.33

Continued—

Appendix—(*Continued*)

84	3150	Electric lamps and lighting equipment	0.65	0.65	0.14	0.16
85	3190	Other electrical equipment n.e.c.	0.65	0.68	0.16	0.17
86	321	Electronic valves and tubes etc.	0.68	0.67	0.22	0.23
87	322	TV, radio and telegraphy apparatus	0.84	0.88	0.83	0.97
88	323	Sound/video apparatus of TV and radio	0.87	0.90	1.00	1.00
89	3311	Medical/surgical/orthopaedic equipment (Ex)	0.73	0.73	0.25	0.28
90	3312	Measuring instruments and appliances	0.82	0.82	0.56	0.68
91	332 & 333	Watches and clocks	0.49	0.75	0.14	0.15
92	3410	Motor vehicles	0.83	0.78	0.50	0.81
93	3420	Bodies for motor vehicles and trailers	0.83	0.84	0.70	0.76
94	3430	Parts and accessories for motor vehicles	0.77	0.78	0.38	0.43
95	3511 &	Building and repair of ships and boats	0.80	0.76	0.51	0.54
	3520 &	Railway locomotives and rolling stock				
	3530	Aircraft and spacecraft				
96	3591	Motorcycles	0.72	0.59	0.24	0.25
97	3592	Bicycles and invalid carriages	0.82	0.82	0.63	0.76
98	3610	Furniture	0.76	0.83	0.42	0.44
99	3691 &	Jewellery and related articles	0.63	0.83	0.20	1.00
	3692	Musical instruments				
100	3693 &	Sports goods	0.77	0.80	0.36	0.39
	3694	Games and toys (Ex)				
101	3699	Other manufacturing n.e.c	0.71	0.71	0.23	0.27
102	37	RECYCLING	0.87	0.75	1.00	1.00
		Mean Efficiency Scores	**0.7412**	**0.7401**	**0.4300**	**0.5050**

* (Ex) indicates an exporting industries.

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