

Effects of Input Composition on Technical Efficiencies of Textile Industries in Pakistan

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This paper studies the technical efficiencies of the textile manufacturing industries in Pakistan using 5-digit level industry data. Technical efficiencies are computed by the Data Envelopment Analysis technique assuming constant as well as variable returns to scale. The efficiency scores thus obtained are analysed by the TOBIT regression technique to determine how input composition influences these efficiency scores. It is found that imported raw material and machinery exercises a positive effect, whereas non-industrial costs affect technical efficiencies in a negative way. Electricity does not play its due role in affecting technical efficiencies.

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1. INTRODUCTION

Pakistan is the fourth largest cotton producing country in the world after China, India and the USA. It is not surprising that Pakistan's industrialisation began in the 1950s with the textile industry at its core. Over the years, the textile sector has maintained its central role in Pakistan's economy. It contributes about 54 percent of the total export earnings of the country, accounts for 46 percent of the total manufacturing sector, and provides employment to 38 percent of the labour force in manufacturing [Pakistan (n.d.)]. Pakistan's textile exports, which were 9.754 billion Dollars in 2009-10, increased to 13.104 billion Dollars in 2010-11, [Pakistan (n.d.), Table 8.1]. The textile policy (2009-14) targets its exports to rise to \$25 billion by the year 2013-14.

Textile industries have certain peculiarities which make them especially suitable for a developing country like Pakistan. First, the raw material used is abundantly available in our agro-based economy. Second, textile industries are labour intensive, and require relatively low level of skill from workers. Uneducated/unskilled men and women

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can also be employed in these industries. Consequently, these industries ease the unemployment problem, alleviate poverty, and promote female empowerment. Third, these industries do not require heavy investment in plants and machinery, making it easier to enter this business. Fourth, they provide a wide range of vertical linkages within various subgroups. Fifth, textiles, especially clothing, both in product material and design are highly value added. Today textile materials have wide variety such as nylon, cotton, polyester, silk, and wool. Special combinations of these materials are used to make high performance clothing and specialty fabrics. Recent developments in microfiber research have opened up new horizons for textile industry. These fibres are especially designed to have desirable attributes of insulation, durability, water and stain resistance etc. They can perform well even in the most demanding situations. Due to these reasons their demand is increasing in areas like sports, military, and industrial clothing.

In view of the importance of the textile sector it would be necessary to explore the factors that contribute to its performance. Empirical research indicates that improvement in technical efficiency is a major contributor to overall factor productivity growth, see e.g. Wadud (2007).

Technical efficiency measures how optimally a firm (or an industry) is using inputs to achieve a given level of output. Normally, a frontier function is estimated to serve as a benchmark against which each firm is compared to get individual efficiency scores. The firms lying on the frontier get a score of one while those lying below this frontier get a score of less than one.

The objective of this paper is to estimate technical efficiency scores of Pakistani textile manufacturing industries and to analyse the factors influencing these efficiency scores. The paper contributes to the empirical literature on technical efficiency of Pakistani textile industries in two important ways. First, we aim to find technical efficiency scores for textile industries *in particular*. Previous studies have measured technical efficiencies of Pakistani textile industries in the broader context of overall manufacturing industries. For example, Din, *et al.* (2007) estimate technical efficiencies of Pakistani manufacturing industries. Their production frontier represents all manufacturing industries. Consequently, their efficiency scores indicate how a particular industry performs in comparison with all other manufacturing industries. This paper constructs the production frontier with reference to textile industries exclusively. Here, efficiency scores indicate how a particular textile industry performs in comparison with other textile industries. Second, this paper goes a step further in exploring the factors which influence these efficiency scores.

From an analytical perspective it would be interesting to observe how technical efficiency behaves in relation to different input compositions. Output is almost always positively affected by inputs (up to certain limits), but how a certain input is used in relation to other inputs may determine whether technical efficiency has increased or decreased.

Returns to scale are important in determining technical efficiency scores. As pointed out by Coelli (1996), in case of constant returns to scale (CRS) we assume that all decision making units (DMUs) are operating at the optimal scale. However, factors like imperfect competition, regulatory requirements and constraints on finance may cause a DMU to operate at less than the optimal level. This fact favours the use of

variable returns to scale (VRS) model. However, the CRS approach has its own advantages. The assumption of CRS allows the comparison between large and small DMUs [Noulas (1997)]. A problem with the VRS model is that in such models where a few large DMUs are present, there is the possibility that the frontier will be dominated by these large DMUs. While in fact these large DMUs may not be efficient [Berg, *et al.* (1991)]. With these considerations we use both the CRS and the VRS assumptions to analyse the data.

The rest of the paper is divided as follows: Section 2 gives a review of theoretical and empirical literature; data, models, and variables are discussed in Section 3; results are discussed in Section 4; and finally Section 5 concludes the paper.

2. REVIEW OF LITERATURE

The theory of production frontier provides a suitable framework for empirical work on technical efficiency. Such work started with Farrell (1957) who used the concept of frontier production function against which the performance of productive units could be compared. Following these early works, many writers tried different techniques to estimate the production frontier and efficiencies. Broadly, these techniques can be divided in two major groups:

- Parametric Techniques, and
- Non-Parametric 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. The usual tests of significance can be performed in these models. Non-parametric techniques, on the other hand, do not require a functional form. They 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) and free disposal hull (FDH) are more commonly used. To keep the analysis simple we shall use a single non-parametric technique viz. DEA assuming both CRS and VRS. The CRS model is attributed to Charnes, Cooper, and Rhodes (1978), while the VRS model was proposed by Banker, Charnes, and Cooper (1984) by imposing an additional convexity constraint to obtain that model.

Once we get technical efficiency scores, the next stage involves the analysis of the factors which may be influencing these efficiency scores. The Ordinary Least Square estimation might appear to be the obvious way. However there is a problem with such estimation; technical efficiency scores are bounded between zero and one, and Ordinary Least Squares with such a dependent variable may predict values greater than one [Coelli, *et al.*, p. 194]. Different techniques have been suggested to solve this problem. This paper follows the technique used by Bjurek, *et al.* (1992), and McCarty and Yaisawarng (1993)

who applied a censored regression model to analyse the technical efficiency scores obtained through application of the DEA technique.

Censored regression models are designed to estimate linear relationships between variables when the dependent variable is bounded by either a minimum value or a maximum value (or both). In the case of censoring from above the dependent variable lies at or below some threshold value. Similarly, in the case of censoring from below, values of dependent variable lie at or above some threshold value. The Tobit model developed by James Tobin (1958) is employed here to analyse the factors influencing efficiency scores.

This two-stage approach of efficiency analysis has been widely used in different areas of empirical research. Oum and Yue (1994) use DEA efficiency scores with a Tobit model to analyse the effects of government intervention and subsidisation on the efficiency of railways systems in 19 OECD countries. Chilingirian (1995) analyses the clinical efficiency of 36 physicians in a single hospital using DEA and a multi-factor Tobit analysis. Luoma, *et al.* (1996) examine the efficiencies of Finnish health centres by applying DEA and the Tobit model to find out how the various economic, structural and demographic factors affect these efficiencies.

During recent years quite a few studies have explored the performance of textile manufacturing activities. Some of these are briefly reviewed below.

Murugeswar (2011) analyses growth in total factor productivity in Indian textile industry. The study is based upon the data collected by Annual Survey of Industries (ASI) and published by Central Statistical Organisation (CSO). There are 6 sub-sectors identified on three and four-digit classification. Cross-sectional and time series data is used for the period 1980-2005. The author estimates Malmquist Productivity Indices, and the break total factor productivity growth in case of change in technical efficiency and change in technology.

Samad and Patwary (2003) estimate technical efficiencies for the textile industry of Bangladesh using translog stochastic production frontier. The study uses panel data for the period from 1988-89 through 1993-94. The data are taken from Census of Manufacturing Industries (CMI) published by Bangladesh Bureau of Statistics (BBS). The value of gross output is taken as the dependent variable whereas, total fixed assets, total number of persons engaged, and the cost of raw material and packaging are used as independent variables. Woolen textiles, jute textiles, and carpets and rugs are found to be highly efficient groups of industries. Cordage, rope and twine, and spooling and thread ball score least in efficiency ranking. The authors attribute these low efficiency scores to low level of technology used in the industries.

Wadud (2004) analyses technical efficiency of Australian textile and clothing firms based on a longitudinal survey covering the period of 1995-1998. The author uses a Cobb Douglas stochastic production frontier to examine firm level technical efficiencies. Analysis of inefficiency effects indicates that firms' age, size, capital intensity, proportion of non-production to total workers and type of legal status significantly affect technical efficiencies of the firms. In a subsequent paper [Wadud (2007)], the author decomposes the total factor productivity growth into changes in technology, changes in technical efficiency, and scale effects. It has been found that changes in technical efficiency mostly dominated the overall growth in total factor productivity in textile and clothing firms.

Din, *et al.* (2007) estimate technical efficiencies of Pakistani manufacturing industries using industry level data from Census of Manufacturing Industries for the years 1995-96 and 2000-01. The efficiencies of textile industries are estimated in the broader context of overall manufacturing industries. The study uses stochastic frontier as well as DEA technique. This technique is used under the assumptions of CRS and VRS. Results show low technical efficiency scores for the textile sector. The average efficiency scores for this sector are 0.12 and 0.30 for 1995-96 and 2000-01 respectively under the assumption of constant returns to scale; whereas, for overall manufacturing industries these scores turn out to be 0.23 and 0.42 respectively.

Khalil (2011) measures technical efficiency of 45 textile processing units located in Karachi. The paper uses data from a survey conducted in 2008. Data envelopment analysis is used to estimate efficiency scores while taking into account both desirable and undesirable outputs (polluting factors which need to be reduced to increase the performance). The results indicate that when undesirable outputs are included in the model, the number of efficient producers increases. From this the author concludes that some producers do give consideration to the reduction in undesirable outputs.

3. DATA AND METHODOLOGY

Data and Variables

The data used in this paper are taken from Census of Manufacturing Industries (2005-06), published by the Federal Bureau of Statistics (now Pakistan Bureau of Statistics). Industries are identified at 5-digit level according to Pakistan Standard Industrial Classification (PSIC), 2007. Twenty-seven industries are included in the analysis.¹ The data used are briefly described below:

Output

Value added reported in CMI reports does not allow for non-industrial costs. However, another variable, contribution to GDP, takes care of industrial as well as non-industrial costs. This definition of output is adopted as it seems more appropriate in the context of the present study.

Capital

Capital consists of all 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. These include land, building, plant and machinery etc.

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.

¹CMI reports 28 textile industries at 5-digits level. One industry, viz., Carpets and rugs (hand made) turned out to be an outlier in preliminary estimation, so it was excluded from the analysis.

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. The raw material given to other establishments for manufacturing goods (semi-finished and finished) on behalf of the establishment is included, whereas raw material supplied by others for manufacturing goods on their behalf is excluded. The CMI gives data on imported raw materials as well as on those domestically produced.

Energy

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

Industrial Costs

The CMI includes cost of the raw materials, fuels and electricity consumed, payments for work done, payments for repairs and maintenance and the cost of goods purchased for resale in the category of industrial costs.

Non-Industrial Costs

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

Methodology

A two-stage methodology is used to analyse technical efficiency at the industry level. In the first stage technical efficiency scores are obtained using the DEA model. In the 2nd stage the effects of various variables are analysed through the TOBIT model. The models are briefly described below:

DEA Model

We use the DEA model to estimate the technical efficiency score under the CRS and VRS assumptions. It is assumed that the industries try to maximise output with a given combination of inputs. Under the assumption of CRS, the following n linear programming problems are solved to get efficiency score for each industry.

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

Where Φ is a scalar, and λ is a vector of constants. X and Y represent input and output matrices for all industries. The symbols y_i and x_i represent output and input vectors of i th industry respectively. The contribution to GDP is used as output. Five inputs are identified viz, labour, capital, raw materials, energy, and non-industrial costs. 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.² It represents the proportional increase in output that could be achieved by the i th industry, with inputs being held constant.

For VRS, additional convexity constraint ($\epsilon \lambda = 1$) is imposed in the model. The VRS model is written as:

$$\begin{aligned} & \text{Max}_{\Phi, \lambda} \Phi \\ & \text{s.t.} \\ & -\Phi y_i + \sum Y \lambda \geq 0 \\ & x_i - \sum X \lambda \geq 0 \\ & \lambda \geq 0 \\ & \epsilon \lambda = 1 \end{aligned}$$

Where ϵ is a vector of one.

The convexity constraint ensures that an inefficient industry is only ‘benchmarked’ against an 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].

These models can be computed by running a linear programme for each industry. This study uses the computer programme DEAP developed by Coelli (1996) to compute technical efficiency scores.

Tobit Model

Since technical efficiency scores are restricted by an upper and lower limit, viz. zero and one, but are continuous between the two limits, the two-limit Tobit model is used here.³ Such a model can be represented in general form by the following equation:

$$z_i^* = \beta' w + \epsilon_i$$

Where z_i^* is unobserved or latent dependent variable. Observed DEA efficiency score of i th industry, denoted by z_i in this model are used in place of z_i^* .

w is a vector of explanatory variables,
 β is a vector of parameters to be estimated, and
 $\epsilon_i \sim N(0, \sigma^2)$ is the random term.

We denote lower limit by L_1 , upper limit by L_2 , such that:

$$\begin{aligned} z_i &= L_{1i} \text{ when } z_i^* \leq L_{1i} \\ z_i &= L_{2i} \text{ when } z_i^* \geq L_{2i} \\ z_i &= z_i^* \text{ when } L_{1i} < z_i^* < L_{2i} \end{aligned}$$

The model is estimated through the Maximum Likelihood technique. The likelihood function of this model is given by:

$$L(\beta, \sigma \mid z_i, w_j, L_{1i}, L_{2i}) = \prod_{z_i=L_{1i}} \psi \left[\frac{L_{1i} - \beta' w_j}{\sigma} \right] \prod_{z_i=z_i^*} \frac{1}{\sigma} \phi \left[\frac{z_i - \beta' w_j}{\sigma} \right] \prod_{z_i=L_{2i}} \left[1 - \psi \left(\frac{L_{2i} - \beta' w_j}{\sigma} \right) \right]$$

²For detail see Coelli, *et al.* (2005), p. 180.

³For details on two-limit TOBIT model, see Rosett and Nelson (1975).

The technical efficiency scores obtained in the first stage of the analysis are used as dependent variable in the following empirical equation.

$$z_i = \beta_0 + \beta_1 MachK + \beta_2 DimpRm + \beta_3 ElecEner + \beta_4 NicTc + u_i$$

Where u_i is the random term.

The variables used in this regression are explained below:

z_i is the dependent variable taking values of the i th industry's technical efficiency scores obtained from the DEA model. It may take values between zero and one. However, in actual practice, the technical efficiency score is never zero. Hence the lower limit in Tobit estimation is fixed at the minimum value.

MachK is the ratio of value of purchase of plant and machinery to total value of capital. This variable is used to measure the effect of new technology in the production process. Other expenditures on capital like land, building, and furniture and fixtures are also essential for production process, but these forms of capital are often used in production activity in indirect ways. New and modern machines are expected to make efficient use of other inputs like raw material and labour. Liberman and Johnson (1999) find that investment in new equipment by Japanese steel firms led to a higher level of labour productivity in comparison with U.S. firms. In contrast, Dijk and Szirmai (2006) find that plants operating under the latest technologies have lower levels of efficiency than mills operating under outdated equipment in the Indonesian pulp and paper industry. But, such behaviour is not likely to occur at industry level. So, we may reasonably expect that this variable will take positive sign in the regression.

DimpRM is the dummy variable used to capture the effect of imported raw material in the production process. The variable takes the value of one if imported raw material is used, zero otherwise. The sign of this variable is an empirical matter. One might expect that imported raw material, being of better quality, would positively affect technical efficiency. Mazumdar, Rajeev, and Ray (2009) find positive effect of imported raw material on efficiency of Indian pharmaceutical firms. However, if the imported raw material happens to be of low quality, or it does not quite suit domestic technology, then its effect on technical efficiency might be negative.

ElecEner is the proportion of cost of electricity to total energy cost used in the industry. Electricity is usually considered a better option than other sources of fuel. This source of energy is highly flexible and convenient. Literature indicates that electricity-intensive technologies have been replacing other energy-intensive technologies (which rely on fossil fuels to a greater extent) in manufacturing [Doms and Dunne (1995)]. A higher proportion of electricity used is expected to influence efficiency in a positive way. However in Pakistan economy, due to shortage of electricity, this important input may not be able to play its due role. Frequent power failures in electric supply and 'load shedding' may result in disruptions in production process, and may even force industrial users to seek other relatively inefficient sources of energy. The sign and significance of this variable may, therefore, be different from what the theory suggests. In other words, the proportion of electricity in total energy used by the industry indicates the level of dependence on electricity. When the supply of electricity becomes unreliable, the industries which depend more on electricity suffer more. This implies possibility of negative relationship between the proportion of electricity in total energy use and efficiency scores.

NicTc is the proportion of non-industrial costs to total costs (industrial and non-industrial). As described above, CMI includes costs like payments for transport, insurance, copy rights/royalties, postage, telephone, fax and internet charges, printing and stationery, legal and professional services, advertising and selling services, travelling in the category if non-industrial costs. However, other costs like corruption, bureaucratic hassles, litigation, and dispute settlements might also be contributing to this type of cost. All these things are expected to cause hurdles in smooth functioning of a business. So, we might expect this variable to take a negative sign.

All variables used in Tobit regression are in the natural logarithmic form. The computer package STATA is used to run the Tobit model.

4. RESULTS

DEA Model

Technical efficiency scores from DEA models are reported in Table 1. The scores obtained through VRS are slightly higher than those through CRS model. This is due to

Table 1

Efficiency Scores of Textile Industries

Industries	CRS	VRS
1 Spinning of Natural Textile Fibres	1	1
2 Spinning of Man-made Staple Fibres	0.823	1
3 Textile Yarn and Thread of Natural Fibres	0.762	1
4 Text. Yarn and Thread of Man-made Staple Fibres	0.57	0.783
5 Processing of Textile Waste	0.38	0.387
6 Fabrics Other than Cotton	0.869	0.923
7 Cotton Fabrics	1	1
8 Fabrics of Man-made Filaments	0.716	0.781
9 Pile Fabrics, Terry Towelling etc.	0.777	0.81
10 Weaving of Fabrics on Khadi /Handloom	0.398	1
11 Finishing of Textile Fibres and Yarn	0.703	0.827
12 Bleaching and Dyeing of Fabrics	0.569	0.612
13 Printing Services of Fabrics	1	1
14 Finishing of Textiles (Khadi/Handloom)	0.97	1
15 Other Textile Finishing n.e.c.	0.242	0.468
16 Made-up Textile Articles for Household	1	1
17 Other Made-up Textile Articles	0.562	0.574
18 Carpets and Rugs (other than by hand)	0.497	0.513
19 Cordage, Rope, Twine and Netting	1	1
20 Embroidery and Zari Work by Hand	1	1
21 Narrow Woven Fabrics and Embroidery	0.588	0.604
22 Other Textiles n.e.c.	1	1
23 Knitted and Crocheted Fabrics	1	1
24 Knitted/Crocheted Cotton Text. Articles	0.553	0.555
25 Knitted/Crocheted Woollen Text. Articles	0.722	0.742
26 Knitted/Crocheted Synthetic Articles	0.356	0.605
27 Knitted/Crocheted Articles n.e.c.	0.703	0.736

the fact that the envelop obtained through the VRS model encloses the data in a more compact way than that from the CRS model. Consequently more observations are likely to lie on or near the frontier. The average technical efficiency turns out to be 0.73 in case of the CRS model and 0.81 in the VRS model. These averages are much higher than those reported by Din, *et al.* (2007). Further comparison shows that efficiency scores for individual industries are also, in general, higher in present study. The reason for this discrepancy is that the mentioned study constructs the production frontiers for the whole manufacturing sector, and the technical efficiencies of textile industries are computed with reference to these general frontiers. In the present study the frontiers are constructed for the textile industries only, and technical efficiency scores are computed with reference to these specific frontiers.

Individual efficiency scores (Table 1) indicate that Cotton Fabrics, Printing Services of Fabrics, Made-up Textile Articles for Household, Cordage, Rope, Twine and Netting, Embroidery and Zari Work by Hand, Knitted and Crocheted Fabrics, and Other Textiles n.e.c. are the most efficient industries. Among the least efficient industries are: Carpets and Rugs (other than by hand), Processing of Textile Waste, Knitted/Crocheted Synthetic Articles, and Other Textile Finishing n.e.c.

There may be a number of causes of these differences in efficiency scores. Unfortunately the CMI data is not detailed enough to undertake an exhaustive analysis of the factors influencing technical efficiencies of all textile industries. The present study limits itself to analysis of the effect of input proportions on efficiency scores; i.e., to explore what type of input proportions are beneficial or detrimental to the efficiencies of textile industries. In the following pages we try to tackle this issue through Tobit analysis.

These efficiency scores are quite high in comparison with Din, *et al.* (2007). As mentioned previously, Din, *et al.* (2007) estimate technical efficiencies of Pakistani manufacturing industries. Their production frontier represents all manufacturing industries. Consequently, their efficiency scores indicate how a particular industry performs in comparison with all other manufacturing industries. This paper constructs the production frontier with reference to textile industries. Here, the efficiency scores indicate how a particular textile industry performs in comparison with other textile industries. Due to fewer variations in the nature of industries, the production points do not lie very far from the frontier. Therefore, these efficiency scores are relatively higher.

Tobit Results

The results of Tobit regressions are reported in Table 2 and Table 3. Table 2 shows the results when DEA scores are obtained under the assumption of constant returns to scale. The Likelihood Ratio (LR) Chi-Square test is conducted to check the null hypothesis that all predictors' regression coefficients are equal to zero. The number in the parentheses indicates the degrees of freedom of the Chi-Square distribution used to test the LR Chi-Square statistic and is defined by the number of coefficients in the model. The null hypothesis is rejected at 0.0242 and 0.0009 levels of significance for CRS and VRS cases respectively. This leads us to conclude that at least one of the regression coefficients in both models is not equal to zero. As argued by Coelli (1996), in CRS we assume that all decision making units are operating at optimal scale. However, there are many factors like imperfect competition, and constraints on finance that may cause a decision making unit to operate at less than optimal level.

Table 2

Tobit Regression Results for Constant Returns to Scale

Log likelihood = -15.70

LR $\chi^2(5) = 11.22$ Prob> $\chi^2 = 0.0242$ Pseudo $R^2 = 0.2632$

crste	Coeff	Standard error	t-values	P> t	95% Confidence Interval	
Constant	-1.48	0.56	-2.63	0.016	-2.66	-0.31
MachK	0.09	0.09	1.03	0.313	-0.91	0.27
Dimprm	0.48	0.26	1.88	0.074	-0.05	1.01
ElectEn	0.26	0.17	1.52	0.143	0.10	0.61
NicTc	-0.47	0.20	-2.35	0.029	-0.89	-0.05

Table 3

Tobit Regression Results for Variable Returns to Scale

Log likelihood = -9.14

LR $\chi^2(5) = 18.63$ Prob> $\chi^2 = 0.0009$ Pseudo $R^2 = 0.5047$

vrste	Coeff	Standard error	t-values	P> t	95% Confidence Interval	
Constant	-1.84	0.51	3.58	0.002	-2.90	-0.76
MachK	0.11	0.06	1.84	0.079	-0.01	0.24
Dimprm	0.65	0.19	3.40	0.003	0.25	1.05
ElectEner	-0.02	0.12	-0.21	0.837	-0.27	0.23
NicTc	-0.54	0.18	-2.98	0.007	-0.92	-0.16

This fact may explain the weak results of the CRS model. The magnitude of Pseudo R^2 also indicates that the VRS model better explains the variations in efficiency scores across industries.

The effect of expenditure on machinery and equipment is positive and significant in case of VRS (Table 3). This is in line with Liberman and Johnson (1999) who find that investment in new equipment by Japanese steel firms led to a higher level of labour productivity in comparison with U.S. firms. The sign of the dummy variable for imported raw material is positive and significant for both CRS and VRS indicating serious issues regarding availability of high quality raw material in domestic market. As mentioned above, Mazumdar, Rajeev, and Ray (2009) also find positive effect of imported raw material on efficiency of Indian pharmaceutical firms.

The proportion of electricity in total energy used has no significant effect on technical efficiency in case of CRS as well as VRS. The sign also turns out to be ambiguous; positive in CRS and negative in VRS. These results indicate that electricity as an efficient form of energy is not playing its due role in our textile industries. In recent years shortages in power supply have adversely affected almost all sectors of the economy. Textile industries are especially hurt due to two reasons. First, they heavily rely on electricity, and second most of them being small scale units find it difficult to produce their own electricity at an affordable price.

The effect of non-industrial costs is also found to be negative. This is probably due to the factors mentioned above viz. corruption, bureaucratic hassles, litigation, and dispute settlements which are contributing to efficiency losses.

The size, sign and significance of the intercept indicate missing factor(s) influencing technical efficiency in a negative way. Unfortunately data on many inputs in the CMI is not detailed enough to include all possible factors. Information on education of entrepreneurs, technical skills of workers, working environment of the factories, labour-management relationships, and grievance resolution procedures are some of the issues about which information is crucial to pinpoint the sources of inefficiencies.

Despite these issues, it must be pointed out that in the complications of the actual world, no regression can provide an exhaustive list of variables affecting technical efficiencies. In fact, studies with significant intercept terms are quite common in the literature on determinants of technical efficiency, see for example, Mazumdar, *et al.* (2009), Wouterse (2008) etc. One of the objectives of this paper is to analyse the effect of input composition on technical efficiencies, and in this regard the exercise is useful.

Like other businesses in Pakistan, textile industries are mostly family-owned enterprises. As pointed by Gani and Ashraf (2005), "The business groups in Pakistan (previously known as twenty-two families) are informal combinations of legally independent business entities run by families. The family patriarch is the dominant shareholder and manager whereas the immediate and distant family-members help operate various firms within the business group". Obviously, when boards of directors and other management structures are riddled with nepotism, efficiency becomes a low priority issue.

5. SUMMARY AND CONCLUSIONS

In this paper we have examined technical efficiencies of textile manufacturing industries in Pakistan using 5-digit level industry data. Technical efficiencies are computed by Data Envelopment Analysis technique under the assumption of constant returns to scale as well as variable returns to scale. The efficiency scores thus obtained are analysed by Tobit regression technique to determine the factors which influence these efficiency scores. DEA results show that Cotton Fabrics, Printing Services of Fabrics, Made-up Textile Articles for Household, Cordage, Rope, Twine and Netting, Embroidery and Zari Work by Hand, Knitted and Crocheted Fabrics, and other Textiles are the most efficient industries; whereas, Carpets and Rugs (other than by hand), Weaving of Fabrics on Khadi /Handloom, Processing of Textile Waste, Knitted/Crocheted Synthetic Articles, and Other Textile Finishing n.e.c. turn out to be the least efficient industries.

In the Tobit model the proportion of machinery in total capital and dummy for imported raw material are found to have positive effect on technical efficiencies, while non-industrial costs as a proportion of total cost have a negative effect. The proportion of electricity to total energy does not seem to play any significant role.

The issue of raw material needs both short-run as well long-run strategies. First, import restrictions on raw material used in textile industries should be removed as a short-run solution. Second, as a long-term strategy domestic production of such raw material should be encouraged through research and development, technology diffusion, and human resource development. Similar policy measures are recommended for

machinery and equipment. The shortage of electricity needs urgent measures. Cheap and reliable supply of electricity is necessary for the survival of our textile industry in present day environment of openness and competition. Eradication of corruption and better governance, especially simplification of bureaucratic and legal procedures, will definitely contribute to efficiency in a positive way.

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