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Efficiency of Indian Manufacturing Firms: Textile Industry as a Case Study

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Abstract

Translog stochastic frontier production functions are fit to firm-level cross-sectional data on India's textile firms for each of five selected years to estimate technical efficiency (TE) of firms. We find that average TE varies between 68 to 84% across these years and that individual TEs vary with firm-specific characteristics such as size and age. Further, public sector firms are found to be relatively less efficient.

Key words: textile industry; technical efficiency; stochastic frontier; Cobb Douglas production function; translog production function

JEL classification: C12; C13; L25

1. Introduction

The major objective of the present paper is to examine some aspects of productivity of Indian industrial firms at the microeconomic level. For this purpose we consider the textile industry as a case study.

The development of the Indian industrial sector has not been a smooth one, at least up to the early 1980s, with its performance experiencing several ups and downs. Interestingly, during this period the domestic industrial sector was protected, through various restrictive laws and regulations, from competition from foreign modern technology-based industries. However, the shocks that the economy experienced in the early 1990s and the economic reforms that were initiated intensively thereafter changed this scenario. Improved performance of the industrial firms is now being called for and efficiency of a unit is now supposed to be a

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prerequisite for growth or even mere survival. In fact, government policies, particularly after 1991, have gradually turned out to be less friendly to inefficient firms, even in the public sector.

This change in the economic scenario and policy has raised some interesting questions. One issue is related to the question of measurement: how is the economic performance—or, to be specific, the efficiency—of a firm to be estimated? The next task is to examine how these efficiency estimates vary with the size and age of firms. Additional queries may also be made, namely whether there is any significant variation in firm-level efficiency across states or across private and public ownership of firms.

These issues are all very pertinent in the changed scenario in India. In this connection we briefly review studies that have been done to estimate levels of technical efficiency (TE) prevailing in various industries in India. Some studies are based on data collected through surveys specifically designed for this purpose (e.g., Little et al., 1987; Page, 1984). Many of the studies are concerned with estimating and explaining variations in TE only in small-scale industrial units by fitting either a deterministic or a stochastic production frontier (e.g., Bhavani, 1991; Goldar, 1985; Neogi and Ghosh, 1994; Nikaido, 2004; Ramaswamy, 1994). A review of other studies in this area may be found in Goldar (1988).

All these studies, however, use data relating to years prior to the economic reforms. For instance, Bhavani (1991) uses data collected under the first Census of Small Scale Industrial Units in 1973 to estimate the TE of firms at the four 4-digit level industries of metal product groups by fitting a deterministic translog production frontier with three inputs—capital, labor, and materials—and observes a very high level of average efficiency across the four groups. Similarly, on the basis of the data made available by the Second All India Census of Small Scale Industrial Units in 1987–1988, Nikaido (2004) fits a single stochastic production frontier, considering firms under all the 2-digit industry groups and using intercept dummies to distinguish different industry groups. He finds little variation in TEs across industry groups and a high level of average TE in each industry group. Neogi and Ghosh (1994) examine the intertemporal movement of TE using panel industry-level summary data for the years 1974–1975 to 1987–1988 and observes TEs to be falling over time.

The studies by Goldar et al. (2004), Lall and Rodrigo (2001), and Mukherjee and Ray (2004), however, relate to the post-reform era. Using panel data for 63 firms in the engineering industry from 1990–1991 to 1999–2000 drawn from the Prowess database (version 2001) of the Centre for Monitoring Indian Economy, Goldar et al. (2004) fit a translog stochastic production frontier to estimate firm-level TE scores in each year. They find the mean TE of foreign firms to be higher than that of domestically owned firms but do not find any statistically significant variation in mean TE across public and private sector firms among the latter group. They then attempt to explain variation in TEs in terms of economic variables, including export and import intensity and the degree of vertical integration. Lall and Rodrigo (2001) examine TE variation across four industrial sectors in India during

1994 and consider TE in relation to scale, location, extent of infrastructure investment, and other determinants. Mukherjee and Ray (2004) analyze the Annual Survey of Industries (ASI) data for the years 1986–1987 through 1999–2000 and find no major change in the efficiency ranking of individual states after the reforms. They also do not find any convergence in the distribution of TE across states, presumably owing to the possibility that the TE of firms in a state tends to be affected also by state-specific factors, such as the local infrastructure and political environment.

We thus find that the relevant efficiency questions raised above have not been examined in detail, at least for the large organized industrial sector of India. This shortcoming motivates the present study. An additional feature of our study is that it is based on official firm-level data collected under the ASI in India and made available electronically. These data, which are quite broad in coverage and yet have remained largely unused, are expensive to purchase and demand substantial processing time. We therefore confine our analysis to one particular industry: the textile industry.

We choose the textile industry for analysis on the grounds that it is one of the oldest industries in India. In fact, it accounted for about 20% of India's total industrial output and about a third of her total industrial employment in 1970–1971. Although these figures have fallen gradually (to respectively 8 and 17% in 1999–2000), they are still substantial. There is another important reason for the selection of the textile industry. Textile is also a major export earning industry. For a long time such exports were guided by the Multi-Fibre Arrangement (MFA) of 1974, which has handled national quotas for exports of textiles. As this act has been dismantled since 2005, it may be interesting to examine whether textile firms have acquired high efficiency within this period. Unfortunately, we can only access firm-level data up to 2001–2002. Another limitation of our data is that we can only consider textile firms in the organized sector (i.e., those covered by the ASI). Since data on the economic activities of textile firms in the so-called unorganized sector are not available regularly, we have to leave out firms in this sector, though this sector is larger than the organized sector.

The paper is organized as follows. In Section 2 we review some important aspects of the governments' industrial policies—both general policies and policies specific to the textile industry. In Section 3 we discuss alternative approaches for measuring the efficiency of a firm. We outline here the existing theory of the stochastic production frontier model—a model that has been used extensively in the literature to estimate TE in firms. Section 4 presents a brief description of our dataset and definitions the variables considered for our empirical analysis. Section 5 presents the empirical results, and Section 6 concludes. More empirical results are presented in the Appendix.

2. Government Industrial Policies and Indian Textile Industry

Efficiency and productivity in the Indian manufacturing sector were supposed to have been inhibited by official policies, e.g., the reservation of production of a large number of items for the small scale sector, high customs tariffs distorting resource allocation and inhibiting the Indian firms' ability to compete in global markets, rigid laws acting as impediments to firms attaining efficient size, frictions faced in establishing and closing down firms in response to normal competitive market dynamics, and various distortions created by the structure of domestic trade taxes and excise duties. Fortunately, policy makers have realized the shortcomings of the earlier strategies and the urgency on the part of the Indian industries to become efficient so as to withstand successfully the pressure of foreign competition (Government of India, 2000–2001, p. 149). Over the years several measures have been taken by the government to help domestic industries achieve efficiency. These include both financial measures, such as rationalization of excise duties, liberalization of tax laws and rates, and reduction of interest rates, and physical measures, such as those meant to remove infrastructural constraints (e.g., inadequate availability of power and limited transport and telecommunication services).

The structure of the textile industry continues to be predominantly cotton-based with about 65% of raw material consumed being cotton. It has three sub-sectors: mills, powerlooms, and handlooms. The latter two are jointly considered the "decentralized sector." Over the years the government has granted many concessions and incentives to the decentralized sector, resulting in a phenomenal increase in the share of the latter. For example, while the mill sector represented 76% of total fabric production 1950–1951, it fell to 38% in 1980–1981 and to just 4% in 2001–2002. The share of the decentralized sector rose correspondingly. In the decentralized sector, the powerloom sub-sector has grown at a faster pace, producing as much as 76.8% of the total fabric output in 2001–2002.

The factors that have contributed to the fast development of the powerloom sub-sector include the government's favorable policies toward the synthetic fabric industry and the ability of this sub-sector to introduce flexibility in the product mix in line with the market situation. In the mid-1980s, a new textile policy was announced to enable the industry to increase the supply of high quality cloth at reasonable prices for both domestic consumption and export. In addition, a Textile Modernization Fund of INR 7.5 billion was created to meet the modernization requirements of this industry. In the early 1990s, the textile industry was delicensed, thereby abolishing the prior government requirement of approval to set up textile units including powerlooms. A Technology Upgradation Fund Scheme was also launched in 1999 to enable the textile units to take up modernization projects by providing an interest subsidy on loans.

Global trade in the textile and clothing industry has long been governed by the MFA, which set national quotas for exports of textiles. India has bilateral arrangements under the MFA with developed countries such as the US, Canada, and countries in the European Union. Almost 70% of India's clothing exports have gone to the quota countries of the US and the European community. However, the World Trade Organization's (WTO's) Agreement on Textiles and Clothing (ATC) of 1995 envisages the dismantling of the MFA over a 10-year period. Thus, after three decades, the textile industry was opened to free competition at the international level from January 1, 2005. The Indian textiles industry is now at the crossroads with the phasing out of a quota regime and the full integration of the textiles sector in the WTO. Most of the studies undertaken to estimate the impact of the ATC on textile trade share find that Asian countries are most likely to benefit from the dismantling of the quotas. They predict a substantial increase in market shares for China and India (see Government of India, 2004–2005, p. 144, for more discussion).

India has a natural competitive advantage in terms of a strong and large multi-fiber base and abundant cheap skilled labor. However, with prices being expected to fall in the post-quota regime, presumably owing to increased international trade and competition, such an advantage may not be enough. Enhanced efficiency and productivity are essential to meet the emerging challenge of global competition. It is against this background that the performance of the Indian textile firms needs to be examined rigorously. That is the major objective of the present study.

3. Model for Measuring Efficiency

Measurement of efficiency of a producing unit effectively started with the analysis of Farrell (1957). A distinction is made between TE and allocative efficiency (AE). In the case of TE, a comparison is made between observed output and the maximum potential output obtainable from the given inputs (an output-oriented efficiency) or between the observed inputs and the minimum possible inputs required to produce a given level of outputs (an input-oriented efficiency). The AE, in contrast, refers to the ability of a firm to combine inputs and outputs in optimal proportions, given their respective prices and production technology (see Coelli et al., 1998, pp.134-140, and Lovell, 1993, p. 40, for detailed discussions).

A substantial literature, both theoretical and empirical, exists using Farrell's (1957) classic definition of TE. Basically there are two alternative methods to measure the TE scores of firms: data envelopment analysis, which involves mathematical programming methods, and the stochastic frontier approach, which involves econometric methods. In this study, we only consider estimation using the stochastic frontier models, which were developed independently by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

To briefly describe this method, consider a stochastic production frontier, $f(X_i;\beta)\exp(v_i)$, which represents the maximum possible output producible with the input vector used by the i th firm, X_i, given the corresponding vector of technology parameters, β, and a random variable seeking to capture all random factors outside the control of this firm (e.g., weather, natural disasters, and strikes) that are likely to affect its maximum possible output, v_i. However, the i th firm's observed output, Y_i, may lie below the frontier output for a variety of reasons, e.g., workers shirking or having lower ability, poor management decisions, or inadequate monitoring efforts (Ray, 2004, pp. 13-14). Such shortfalls are then attributed to the presence of technical inefficiency in the firm. Since the actual output can be no more than the frontier output, we may write:

$$Y_i = f\left(X_i;\beta\right)\exp(v_i)\exp(-u_i)\,, \tag{1}$$

with $u_i \geq 0$ implying that $\exp(-u_i) \leq 1$. A measure—or, as it is called in the literature, an output-oriented Farrell measure—of the TE of the i th firm, TE_i, is then given by the ratio of the actual output to the frontier output:

$$TE_i = \frac{Y_i}{f(X_i;\beta)\exp(v_i)} = \exp(-u_i)\,, \tag{2}$$

for $u_i \geq 0$. Since $\exp(-u_i) \cong 1-u_i$, the TE_i varies inversely with u_i and lies between 0 and 1. The maximum value 1 is attained when $u_i = 0$, i.e., there is no inefficiency. Alternatively, u_i may be taken as an index of inefficiency.

To estimate the magnitude of technical inefficiency prevailing across firms in the particular industry in question, we follow the procedure of Battese and Coelli (1993) and Lundvall and Battese (2000). It may be noted that in (1) there are two error terms. One is u_i, a non-negative random variable introduced so as to measure the magnitude of technical inefficiency in production prevailing in the i th firm. The other is the usual error term, v_i. It is assumed that the v_i are independently, identically normally distributed with mean zero and variance σ_v^2, and the u_i are independently distributed from a normal distribution with mean μ_i and variance σ_u^2 truncated at zero. Further, the v_i and u_i are assumed to be independent of each other.

Several empirical studies have investigated the determinants of TEs at the firm level through a two-stage procedure. In the first stage, efficiency indices for individual firms are estimated by fitting a stochastic frontier, and in the second stage, the estimated efficiency levels are regressed on firm-specific factors (see, for an example in the Indian context, Goldar et al., 2004, and Nikaido, 2004). Such an approach has, however, been argued to suffer from an inconsistency of assumptions (see Coelli et al., 1998, pp. 207-209, and Kumbhakar and Lovell, 2000, pp. 262-264, for discussion of this point and for references to other relevant studies).

An alternative approach, developed by Battese and Coelli (1993), seeks to estimate and explain firms' efficiency at the same time. We follow this approach here. This approach consists of adding to (1) the following relation explaining the inefficiency of the i th firm in terms of a vector of firm-specific variables, z_i, and then estimating the vector of associated parameters, δ, along with the parameters of frontier production function through a single-stage maximum likelihood method. The mean technical inefficiency is thus written:

$$\mu_i = \delta' z_i\,, \tag{3}$$

where δ' is the transpose of δ. This assumption is consistent with the assumption that u_i comes from a truncation of $N(\delta' z_i, \sigma_u^2)$. Further, for this type of specification, we can easily obtain the density function of u_i conditional on $\varepsilon_i = v_i - u_i$ as well as the expected value of TE_i given ε_i, i.e., $E[\exp(-u_i) \mid \varepsilon_i]$ (for details, see Battese and Coelli, 1988, 1993).

4. Descriptions of Variables, Data, and Model

We use micro-level data for our study, i.e., data on a number of variables for different individual industrial units collected by the Central Statistical Organization (CSO) of the Government of India through its ASI. Our data, a subset of the ASI dataset, are not available in a published form, but can be obtained electronically from the CSO. To fit the stochastic frontier function, we consider data for each of the five selected years, 1985–1986, 1990–1991, 1996–1997, 1998–1999, and 2001–2002, for firms in entire textile industry, which covers units related to the production of cotton, woolen, silk, terrycotton, and other natural fibers like jute, coir, and mesta.

We use five variables in our empirical analyses. These variables are defined below with the corresponding notation to be used. Definitions of concepts like ex-factory value, fixed asset, and manday are as used by the CSO. It would have been very useful if we had panel data. However, the insufficient information prevented constructing panel firm-level data over the years.

Output:	total ex-factory value of products and by-products produced by the firm during the year in question (denoted Y).
Intermediate inputs:	nominal value of inputs (both indigenous and imported, including power and fuels) used by the firm during the year (denoted alternatively X_1 or I).
Capital:	net value of fixed assets of the firm at the beginning of a year (denoted alternatively X_2 or FA).
Labor:	total number of mandays worked during the year (denoted alternatively X_3 or L).
Age:	difference between the current year and the firm's initial production year.

As indicated above, we use a stochastic frontier production function model along the lines of Battese and Coelli (1993, 1995) and Lundvall and Battese (2000) and estimate the parameters of the frontier function (1) simultaneously with those of (3), which seeks to explain technical inefficiency in terms of the firm-specific variables. The stochastic frontier production function used for the econometric analysis is, however, taken to be of the following translog form owing to its flexible nature:

$$\ln Y_i = \left\{ \beta_0 + \sum_{j=1}^{3} \beta_j x_{ji} + \sum_{j\leq}^{3} \sum_{k=1}^{3} \beta_{jk} x_{ji} x_{ki} \right\} + \left(v_i - u_i \right). \tag{4}$$

Here, the subscript i refers to the i th firm, $i = 1, 2, ..., n$, where n is the number of firms in the industry, X_{ji} is the amount of the j th input used by the i th firm, and x_{ji} is the natural logarithm of X_{ji}, $j = 1,2,3$. The mean of the u_i is postulated to be determined by:

$$\begin{aligned} \mu_i = \delta_0 &+ \delta_1 \ln I_i + \delta_2 \ln Age_i + \delta_{11} \left(\ln I_i\right)^2 + \delta_{22} \left(\ln Age_i\right)^2 \\ &+ \delta_{12} \left(\ln I_i\right)\left(\ln Age_i\right) + \delta_{01} D_1 + \delta_{02} D_2, \end{aligned} \tag{5}$$

where D_1 and D_2 are two dummy variables used to distinguish firms located in two groups of Indian states and under two different ownership patterns, respectively. These dummies are explained in detail when we discuss empirical results.

The amount of intermediate inputs, I_i, is used as a proxy for the size of a firm as in Lundvall and Battese (2000). Further, this variable is used both as an input in the frontier production function and also as one seeking to explain deviations from the same frontier owing to technical inefficiency. Such a practice of using the same variable in the production function and in the inefficiency model is not uncommon in the efficiency literature (see Battese and Borca, 1997; Huang and Liu, 1994; Lundvall and Battese, 2000). As shown in Battese and Borca (1997), for the distributional assumptions made here about the random term u_i, the elasticity of the TE with respect to a given explanatory variable, X_i, is given by:

$$\left\{ \frac{1}{\sigma_u} \left[\frac{\varphi\left(\frac{\mu_i}{\sigma_u} - \sigma_u\right)}{\Phi\left(\frac{\mu_i}{\sigma_u} - \sigma_u\right)} - \frac{\varphi\left(\frac{\mu_i}{\sigma_u}\right)}{\Phi\left(\frac{\mu_i}{\sigma_u}\right)} \right] - 1 \right\} \frac{\partial \mu_i}{\partial \ln X_i}, \tag{6}$$

where $\varphi(\cdot)$ and $\Phi(\cdot)$ are, respectively, density and distribution functions of a standard normal variable, X_i is either I_i or Age_i, and $\partial\mu_i / \partial \ln X_i$ is to be computed from (5).

5. Empirical Results

The maximum-likelihood estimates of the parameters of the frontier model defined by (4) and (5) are obtained for each of the five years using the computer program Frontier (version 4.1) described in Coelli (1994). We first obtain the parameter estimates without using any dummy variable in (4) and (5) and estimate the level of the TE of each firm in each sample year. We observe that these estimates vary considerably across firms.

India is a vast country with a number of states and union territories with distinctive sociological, economic, political, and infrastructural features. Hence, one might be interested to know whether the TEs of firms vary significantly across these different geographical regions. We tried, therefore, to examine this issue by considering a number of alternative grouping of states and using intercept dummy variables to distinguish the different groups. Preliminary results indicated that one intercept dummy would be sufficient. As a result we consider one state dummy, D_1, that takes the value 1 if the i th firm is located in Gujrat, Maharashtra, Karnataka, or Kerala and 0 otherwise.

Another factor that might lead to some variation in TEs across firms is the ownership structure. The Indian economy, being of mixed type, has both government-owned and private firms in almost all the important sectors of the economy, and the textile industry is no exception. For instance, about 12% of the textile firms in 1985–1986 were in the public sector, producing more than one fifth of the total output of this industry. Fitting the stochastic frontier model defined by (4) and (5) to the data and estimating the TE of each textile firm, we observed that the estimated TEs of public sector firms are in general lower than their private counterparts (results not shown). This prompted us to introduce a dummy variable, D_2, that takes the value 1 if the i th firm is in the public sector and 0 otherwise.

Using these two dummies for (5), the model was re-estimated and the corresponding regression results are given in Table 1. It may be noted that (5) explains μ_i, the mean of the inefficiency variable u_i. Hence, a higher μ_i indicates a lower expected value of TE. We find from Table 1 that the state dummy is negative for some years, particularly before 1991, but positive for later years. This might indicate that the group of states which had fared better earlier have now lagged behind in general. Of course, a clear picture can emerge only a thorough exploration of alternative groupings of states for each year—an exercise we have not done here. So our result is only tentative. From Table 1 we also find that the ownership dummy D_2 is positive for all years and significant for almost all years, implying that, other things remaining unchanged, a private sector firm is relatively more efficient than a public sector firm.

From Table 1 one notes that some individual parameter estimates are not statistically significant. However, the decision to reduce the number of variables and corresponding parameters should be based on hypothesis tests for inclusion or exclusion of explanatory variables. Results of such tests are presented in Table 2, which gives the values of the generalized likelihood-ratio (LR) test statistic under different null hypotheses for the various parameters. The first row of Table 2 shows that, given the assumption of a translog production frontier, the LR test rejects the Cobb-Douglas function. Thus the input elasticities are likely to depend on the estimated values of the parameters as well as on the levels of the explanatory variables.

Since we fit a translog function, we must check whether the fitted function is well behaved. This is usually done by checking two things: monotonicity (i.e., non-negative input elasticities for each input) and quasi-concavity (i.e., negative semi-definite bordered Hessian of first and second derivatives) for a majority of observations. We computed these quantities (see Tables 3 and 4) and find these two regularity conditions to be satisfied at the sample mean as well as at the majority of the observations for each year except for 1998–1999, for which the percentage of firms satisfying quasi-concavity is relatively low. Hence, our results for this year may not be robust.

Table 1. Estimated Regression Results (with State and Ownership Dummy Variables)

		Estimated Parameter Values				
Variable	Parameter	1985–1986	1990–1991	1996–1997	1998–1999	2001–2002
Constant	β_0	9.57 (19.83)	5.92 (28.61)	9.67 (13.15)	11.23 (14.09)	2.97 (6.15)
$\ln I$	β_1	−0.78 (−11.13)	−0.095 (−2.94)	−0.537 (−6.06)	−0.82 (−7.65)	0.63 (8.3)
$\ln FA$	β_2	0.23 (8.97)	0.12 (6.71)	0.337 (7.80)	0.23 (3.45)	−0.08 (−1.76)
$\ln L$	β_3	0.72 (19.01)	0.56 (22.38)	0.349 (4.64)	0.72 (6.96)	0.314 (4.46)
$(\ln I)^2$	β_{11}	0.09 (33.32)	0.06 (35.08)	0.066 (15.65)	0.08 (16.95)	0.015 (3.38)
$(\ln FA)^2$	β_{22}	0.012 (8.37)	0.007 (7.34)	0.011 (6.64)	0.003 (1.26)	0.0007 (0.55)
$(\ln L)^2$	β_{33}	0.025 (6.44)	0.029 (11.45)	0.02 (3.95)	0.02 (3.93)	0.017 (3.25)
$\ln I \times \ln FA$	β_{12}	−0.034 (−12.75)	−0.016 (−9.43)	−0.0315 (−6.95)	−0.03 (−3.8)	0.0045 (0.92)
$\ln FA \times \ln L$	β_{23}	0.0004 (0.11)	−0.0018 (−0.78)	−0.006 (−1.37)	0.02 (2.48)	−0.0002 (−0.04)
$\ln I \times \ln L$	β_{13}	−0.072 (−15.13)	−0.062 (−20.11)	−0.036 (−4.68)	−0.08 (−8.95)	−0.033 (−3.92)
Constant	δ_0	9.85 (16.24)	11.33 (13.18)	46.62 (5.02)	5.93 (4.6)	−25.85 (−3.99)
$\ln I$	δ_1	−0.87 (−12.47)	−1.365 (−9.79)	−4.77 (−4.40)	−0.24 (−1.43)	2.63 (3.99)
$\ln Age$	δ_2	−0.556 (−3.04)	−0.40 (−3.92)	−2.80 (−2.65)	0.007 (0.03)	1.87 (2.99)
$(\ln I)^2$	δ_{11}	0.004 (1.73)	0.027 (5.63)	0.077 (2.66)	−0.02 (−4.13)	−0.08 (−4.93)
$(\ln Age)^2$	δ_{22}	0.09 (5.02)	0.16 (11.01)	0.92 (5.84)	0.18 (6.08)	0.16 (3.29)
$\ln I \times \ln Age$	δ_{12}	0.0156 (1.06)	−0.015 (−1.73)	−0.085 (−1.72)	−0.036 (−2.27)	−0.138 (−4.17)
D_1	δ_{01}	−0.20 (−4.11)	−0.255 (−8.21)	0.101 (2.63)	0.977 (8.44)	0.625 (7.32)
D_2	δ_{02}	0.929 (12.41)	1.78 (12.13)	1.23 (1.27)	1.57 (12.56)	1.86 (11.95)
	$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.66 (24.28)	0.60 (17.5)	10.16 (12.63)	1.21 (11.88)	1.27 (11.82)
	$\gamma = \sigma_u^2 / \sigma^2$	0.91 (201.55)	0.96 (435.67)	0.995 (2351.5)	0.96 (214.23)	0.98 (432.3)
Log-Likelihood Value		−2502.49	178.27	−2917.25	−678.92	−254.1
Number of observations		5546	4750	3598	1423	1748
Mean TE		0.73	0.84	0.68	0.76	0.80

Notes: *t*-statistics are in parentheses.

Table 2. Generalized Likelihood Ratio Tests in the Estimated Stochastic Frontier

Null Hypothesis	Estimated Generalized Likelihood Ratio Statistics					Critical Values	
	1985–1986	1990–1991	1996–1997	1998–1999	2001–2002	1%	0.5%
$\beta_{jk}=0$ for $j,k=1,2,3$ (Cobb-Douglas function)	2437.4	2175.9	542.36	190.48	54.42	16.81	18.5
$\gamma=\delta_0=\delta_1=\delta_2=\delta_{11}$ $=\delta_{22}=\delta_{12}=\delta_{01}=\delta_{02}=0$ (no inefficiency effect)	1818.96	2135.84	3958.78	449.22	501.66	20.97[a]	22.88[a]
$\delta_1=\delta_{11}=\delta_{12}=0$ (no size effect)	1963.84	634.8	3974.64	178.78	50.9	11.34	12.8
$\delta_2=\delta_{22}=\delta_{12}=0$ (no age effect)	11.68+	23.48	24.28	29.7	7.3**	11.34	12.8
$\delta_1=\delta_2=\delta_{11}=\delta_{22}=\delta_{12}=0$ (no size and age effect)	1980.54	645.04	3976.46	155.46	51.4	15.09	16.7
$\delta_{01}=0$ (no state variation)	6.8+	5.76*	3.94*	23.76	5.34*	6.64	7.88
$\delta_{02}=0$ (no ownership variation)	100.24	169.58	5.48*	39.3	27.6	6.64	7.88
$\delta_{01}=\delta_{02}=0$ (neither state nor ownership variation)	114.1	172.42	0.30	65.02	36.0	9.21	10.6

Notes: +, *, and ** denote significance at 1%, 5%, and 10% levels, respectively. All other values are significant at the 0.5% level except the last one for the year 1996–1997, which is insignificant. [a]The critical value for the test involving γ is taken from Table 1 of Kodde and Palm (1986, p. 1246).

Table 3. Percentage of Firms with Non-Negative Input Elasticity

Inputs	Percentage of Firms				
	1985–1986	1990–1991	1996–1997	1998–1999	2001–2002
Intermediate Input	100	100	100	99.93	100
Fixed Asset	87	97	95	68	96
Mandays	95	95	90	83	99

Table 4. Percentage of Firms Satisfying Regularity Conditions

Regularity Condition	Percentage of Firms				
	1985–1986	1990–1991	1996–1997	1998–1999	2001–2002
Monotonicity	86	93	86	68	94
Quasi-Concavity	68	80	58	33	87
Both	68	80	58	33	87

The second row of Table 2 shows rejection of the null hypothesis of no technical inefficiency among firms for each year. Thus, given that the technology can be described by a translog stochastic frontier, firms can not be supposed to be technically efficient. The parameter $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$ measures the proportion of the total variability in output (across firms with the same values of inputs) due to variation in TEs. With estimates of γ between 0.91 and 0.995, most variability in output in each year is due to variation in technical inefficiency in production.

The next three tests reported in Table 2 are concerned with hypotheses involving restrictions on the size and age parameters in the inefficiency model. The null hypotheses of no size effect or of no age effect are almost all rejected at the 0.5% level for all years. The last three tests seek to ascertain whether the firm-level TE varies significantly across different groups of states and/or different ownership structures. As reported earlier, we consider only intercept dummies to investigate these issues and find from Table 2 that the null hypotheses of no state or ownership variations are all rejected except in one year.

For each year TEs of the different firms are computed and an average across firms is then calculated in the last row of Table 1. We observe that the average TE of firms ranges from 0.68 to 0.84. Histograms of TEs of individual firms (not shown here) are negatively skewed.

Table 5. Distribution of Mean Technical Efficiency by Size Group of Firms for Different Years

Group Size (in deciles)	Mean Technical Efficiency				
	1985–1986	1990–1991	1996–1997	1998–1999	2001–2002
Lowest 10%	0.33	0.64	0.44	0.49	0.76
10–20%	0.51	0.74	0.60	0.68	0.76
20–30%	0.64	0.80	0.61	0.71	0.75
30–40%	0.73	0.84	0.64	0.71	0.76
40–50%	0.80	0.87	0.69	0.75	0.79
50–60%	0.83	0.89	0.72	0.83	0.80
60–70%	0.85	0.90	0.75	0.84	0.83
70–80%	0.87	0.91	0.76	0.86	0.85
80–90%	0.885	0.91	0.78	0.86	0.86
Highest 10%	0.887	0.90	0.75	0.87	0.87
All Firms	0.73	0.84	0.68	0.76	0.80

Table 6. Distribution of Mean Technical Efficiency by Age Group of Firms for Different Years

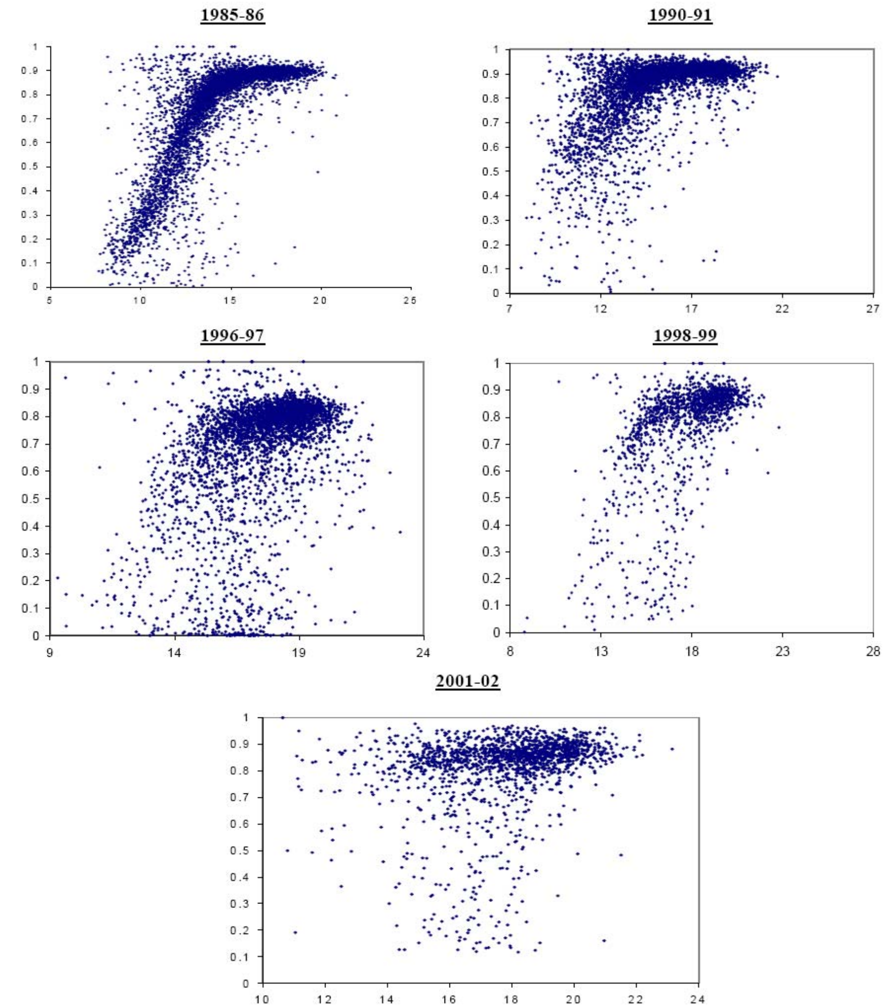
Age Group	Mean Technical Efficiency									
	1985–1986		1990–1991		1996–1997		1998–1999		2001–2002	
	% of Firms	Mean TE	% of Firms	Mean TE	% of Firms	Mean TE	% of Firms	Mean TE	% of Firms	Mean TE
Very Old	30.9	0.735	30.3	0.829	26.3	0.671	35.7	0.734	31.2	0.782
Old	27.3	0.725	28.5	0.836	28.3	0.681	29.3	0.764	32.3	0.805
Young	41.8	0.737	41.3	0.851	45.4	0.675	35.0	0.784	36.5	0.821
All Firms	100.0	0.73	100.0	0.84	100.0	0.68	100.0	0.76	100.0	0.80

Table 7. Mean Elasticity of Technical Efficiency with respect to Size and Age

Variables	Mean Elasticity of Technical Efficiency				
	1985–1986	1990–1991	1996–1997	1998–1999	2001–2002
Size	0.1203	0.0457	0.0589	0.0665	0.0216
	(0.002)	(0.001)	(0.001)	(0.002)	(0.0005)
Age	−0.0085	−0.0155	−0.0051	−0.0344	−0.0183
	(0.0006)	(0.0007)	(0.001)	(0.0026)	(0.0009)

Notes: Standard errors are in parentheses.

Figure 1. Scatterplots of Firm Size (horizontal axis) and TE Score (vertical axis)



An important aspect of our inquiry is to ascertain how a firm's size and age affect its TE score. To examine the first relationship, we first use (6) to compute the elasticity of the TE with respect to size for each firm and year. For each year we then average these values across firms to find mean elasticity and also compute its standard error. Mean elasticities for different years, given in Table 7, are all positive and significant. An example of the interpretation of this elasticity is that if the size in terms of intermediate inputs doubles, the elasticity estimate for the year 1985–1986 implies an increase of TE by about 12%. Hence, a firm with a TE score of 0.50 would do slightly better at a TE score of 0.56, ceteris paribus.

We also examine the relationship between firm size and TE in another way. For each year, individual firms are arranged in ascending order of size as measured by the value of intermediate inputs used, and then the firms are classified into different decile groups. The mean TE of each decile group is then computed. The results of this exercise are given in Table 5. We observe that every year, except in one or two decile groups, the mean TE score increases uniformly with firm size, pointing to a positive relationship between the two. Finally, we consider scatterplots of firms' TE scores and sizes for different years in Figure 1. Although the shapes of the scatterplots differ, the positive association between the two is obvious.

Turning to the relationship between a firm's age and TE score, we classify firms as very old, old, or young if they were established more than 20 years ago, between 10 and 20 years ago, or in the last 10 years. For each year the mean TE of firms in each age group is presented in Table 6, which shows that mean TE tends to be slightly higher for younger firms. This can also be seen by the values of mean elasticities of TE with respect to firm's age for each year in Table 7, which are all negative and significant. Thus we find that, broadly speaking, TE tends to be lower for an older firm. We do not present the scatterplots of firms' TE scores and ages since no clear patterns emerge.

6. Conclusion

The unit-level data on industrial firms in India collected and compiled officially under the ASI are quite broad in coverage and rich in content but have remained largely unexploited to date. The purpose of the present study is to examine microeconomic features of Indian industries on the basis of these data for selected years. We consider five years with gaps of between two and six years: 1985–1986, 1990–1991, 1996–1997, 1998–1999, and 2001–2002. We choose the textile industry as a case study on the grounds that it is one of the largest industries in India. One issue we investigate is descriptive in nature. How does performance—or what is our prime concern, TE—vary across firms in this industry? Further we wish to address whether there is any variation in firm-level efficiency across different regions and whether private firms are more efficient than their public counterparts. These latter two issues in particular have important policy implications, as government officials are now very much concerned with reducing regional disparity and with improving performance of the public sector undertakings. Our empirical study finds evidence of significant differences in both comparisons.

Our methodology—fitting a translog production frontier—permits us to explore how observed variation in TEs vary may be explained in terms of firm-specific factors. Our results support the argument that efficiency has something to do with size: a large firm may have an easier access to cheaper or superior quality of inputs or may enjoy greater economies of scale. However, we do not find evidence that older firms tend to be more efficient. Despite postulated advantages of being more established, such as that an older firm may have easier access to finance, smoothly-functioning buyer-supplier linkages, and more experience, and counter arguments, such as that young firm may have assets of later generations and a fresher workforce (see Lall and Rodrigo, 2001), our empirical results point to an inverse relationship between a firm age and TE score for each year considered.

A question that we have postponed addressing is: has the process of economic reform initiated in the early 1990s made any perceptible impact on the efficiency levels of textile firms? An answer to this question is not easy to obtain from the data we have and the type of exercises that can be carried out with these data. For instance, in order to investigate this issue, one needs panel data, i.e., data on a number of relevant variables corresponding to a given set of firms for several years. Only then may one examine how the extent of efficiency of a given firm or a group of firms has undergone changes. Unfortunately, we do not have panel data on Indian firms. It is therefore quite likely that the firms that we are examining in different years may be different or that the firms that we observe in a year are the relatively better firms, the inefficient firms having failed to survive.

Under these circumstances one may estimate average TE of firms existing in a given year and try to examine whether such efficiency has any time trend. Carrying out this exercise we observe that there is no distinct trend in the average TE of textile firms over the years. It has only fluctuated. However, one point seems to be borne out by our exercises, namely that the average TE has shown some improvement if we study only the post-reform years. It is estimated to increase from 0.68 in 1996–1997 to 0.76 in 1998–1999 to 0.80 in 2001–2002.

Appendix

A limitation of the conventional stochastic frontier approach is that it takes the corresponding input coefficients to be the same for all firms and measures inefficiency by allowing for random changes in the intercept term. It is argued that there may be diversity in individual firms' methods of input application so that the coefficients of a given input may vary across producing units. Swamy (1970, 1971) introduced such a random coefficient regression model (RCRM). Kalirajan and Obwona (1994) and Kalirajan and Shand (1994) sought to popularize this model by bringing in cross-sectional heterogeneity in slopes and intercepts.

Specifically, let there be K inputs and F firms and let Y_f and X_{kf} be the logarithm of output and of the k th input used by the f th firm. They postulate that:

$$Y_f = \sum_{k=1}^{K} X_{kf}\beta_{kf} + \varepsilon_f = X'_f\beta_f + \varepsilon_f\ ,\ f = 1,2,...,F\ , \tag{A1}$$

where $\beta_f = (\beta_{kf})$ and $X_f = (X_{kf})$ are K-component column vectors and ε_f is an error term. Each firm's parameter vector β_f is assumed to vary from the mean vector $\overline{\beta}$ by a vector of random errors as $\beta_f = \overline{\beta} + \nu_f$. With suitable assumptions and methods, stable estimates of $\overline{\beta}$ and the variance-covariance matrix of ν_f can be obtained. Kalirajan and Obwona (1994) define β_k^* , $k = 1,2,...,K$, to be the estimates of the parameters of the frontier production function yielding the potential output and define the potential output of the k th firm to be $Y_f^* = \sum_{k=1}^{K} X_{kf}\beta_k^*$, where $\beta_k^* = \max\ \beta_{kf}$, $k = 1,2,...,K$. The TE of the f th firm is then estimated to be the ratio of $^f\exp(Y_f)$ to $\exp(Y_f^*)$.

However, the RCRM method is not very widely used. An additional problem for us is that the available software can only handle about 220 observations (and that with a only a few explanatory variables), while in any year the number of firms in our sample far exceeds 1,400. To illustrate the method, however, we consider the data for 2001–2002. To get a representative sample, we initially arrange all firms in ascending order of their size and classify them into 100 percentile groups. From each group we then select two firms from the middle of the group so that the number of firms comes out to be 206. We have then fit a Cobb-Douglas frontier by both the RCRM and the stochastic frontier model (SFM) to this sampled dataset.

The results are given in the Table A1. We find that although the mean TE of firms using RCRM is much lower than that using SFM, there is hardly any difference in the estimated frontier coefficients. Computing firm level TE, we also observe a high positive correlation between estimates of individual TEs obtained under the two methods. We could not, of course, verify whether this result would carry through if we could apply the RCRM to the entire dataset rather than only selection. We note recent efforts to merge the two techniques into one (see, e.g., Tsionas, 2002; Huang, 2004). But that is beyond the scope of the present study.

Table A1. Frontier Coefficients Estimated for 2001–2002 by Alternative Methods

	RCRM	SFM
Intercept	0.71	1.02 (6.09)
Inputs	0.97	0.916 (46.79)
Fixed Assets	0.01	0.019 (1.29)
Mandays	0.04	0.06 (3.01)
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	—	0.24 (8.08)
$\gamma = \sigma_u^2/\sigma^2$	—	0.91 (36.1)
Log Likelihood	—	−42.02
Breush-Pagan χ^2 value with 3 degrees of freedom	104.56	—
Mean TE (%)	51	74

Notes: *t*-statistics are in parentheses.

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