Technical Efficiency of Indian Pharmaceutical Firms: A Stochastic Frontier Function Approach

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Abstract

Based on the framework of Battese and Coelli (1992), we estimate the stochastic frontier production function for 76 Indian pharmaceutical firms during 1991-2003. The stochastic frontier production function model with time-varying firm effects reveals that for the pharmaceutical industry as a whole, the technical efficiency has improved over the period 1991 to 2003. The patenting firms are found to be more technically efficient than their non-patenting counterparts. We find constant returns to scale for the full sample and the sub-sample of non-patenting firms, but increasing returns to scale for the firms engaged in R&D and patenting activities.

Key words: Technical efficiency, stochastic frontier production function, pharmaceuticals

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I. Introduction

The pharmaceutical industry in India is going through a period of transition driven by a combination of external forces and internal productivity challenges. On the one hand, the Uruguay Round of Trade Negotiations of the General Agreement of Tariffs and Trade (GATT) has sought to strengthen the patent protection provided to pharmaceutical products in countries like India and on the other hand, economic reforms in India have sought to deregulate the pharmaceutical industry through lesser price controls. The Indian Patent Act, 1970 provided only for process patents in the field of pharmaceuticals, but with the establishment of the World Trade Organization (WTO) in 1995, India is bound to provide for both product and process patents for pharmaceuticals by 2005. Thus, the Indian pharmaceutical firms have to gear up to the challenge of facing competition from pharmaceutical multinational companies (MNCs), because now these MNCs can launch new drugs in the domestic market without fear of being imitated and sold at cheaper rates by the Indian firms.

Further, the decade of the 1990s saw major policy changes for the pharmaceutical industry in India. These included greater liberalization of import policies, foreign equity participation and price decontrol. In 1994, the New Drug Policy was announced which pruned the list of controlled drugs, allowed imports of bulk drugs and foreign direct investment (FDI) up to 51 percent. The greater competition heralded by deregulation in turn led to greater consolidation in the industry and the 1990s saw a wave of mergers and acquisitions. Thus, the conventional perception of jobs and financial security in the pharmaceutical industry sector has been redefined and reshaped. While historically, this

sector has been relatively immune to major economic downturns, earning the reputation as a "recession proof" safe harbour, the industry is now witnessing major downsizing and lay-offs. However, the emphasis on greater R&D expenditures has driven up the demands for biomedical research scientists across multiple disciplines at all levels. Thus, it seems that in the new business environment, the demand for skilled personnel will grow.

The 1990s also saw a great advance in the process of pharmaceutical R&D through 'combinatorial chemistry', computer-aided experiments and biotechnology. These new techniques require smaller highly-focused firms, thereby lowering the minimum efficient scale for pharmaceutical research (Mahlich and Roediger-Schulga, 2001). Thus, the scientific advances in the R&D process itself may be a major contributor to the increased efficiency in the pharmaceutical industry.

This paper attempts to estimate the technical efficiency of pharmaceutical firms using stochastic frontier production function for the industry as a whole and for sub-samples of patenting and non-patenting firms. We compare the efficiency of patenting and non-patenting pharmaceutical firms by using maximum likelihood estimates of the stochastic frontier production functions. The paper contributes to the literature on technical efficiency by using an unbalanced firm-level panel data for Indian pharmaceutical firms and examining the impact of stronger patent protection and deregulation on their efficiency. The paper is organized as follows: Section 2 outlines the methodological framework, section 3 discusses the data sources, section 4 analyzes the empirical results and section 5 concludes.

II. Methodological framework

Technical inefficiency is not only a reality but at sometimes exists widely. Recognizing this, Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) introduced the stochastic production frontier model, which is a significant contribution to the econometric modelling of production and estimation of technical efficiency of firms in an industry. The stochastic frontier has two random components; one is associated with the presence of technical inefficiency and other being a random error. Applications of frontier functions have involved both cross-sectional and panel data. These studies have considered various estimators for parameters of these models.

The concept of the technical efficiency of firms is important for the development and application of econometric models of frontier functions. Although technical efficiency may be defined in different ways (see Fare, Grosskof, and Lovell, 1985), we consider the definition of the technical efficiency of a given firm (at a given time period) as the ratio of its mean production (conditional on its levels of factor inputs and firm effects) to the corresponding mean production if the firm utilized its levels of inputs most efficiently (Battese and Coelli, 1988). We have considered a stochastic frontier production function model for panel data, in which technical efficiencies of firms may vary over time.

This paper adopts the panel data model proposed by Battese and Coelli (1992). The detailed specification of the stochastic frontier model for estimating firm-specific technical inefficiency is well depicted in their paper. We have given a summary of the main structure of the model. We have considered a stochastic frontier production function with exponential specification of time-varying firm effects given as follows:

$$Y_{it} = f(X_{it}, \alpha, t)\exp(v_{it} - u_{it}) \quad (1)$$

$$\boldsymbol{u_{it} = \zeta_t u_i = \{\exp(-\eta(t-T))\}u_i}, \text{ where } \boldsymbol{\zeta_t = \exp(-\eta(t-T))} \quad (2)$$

where i indexes firms and t indexes time. Y_{it} is the output, X_{it} is a vector of inputs and α is a vector of parameters to be estimated. On the one hand, the error term v is distributed as $\mathrm{N}(0, \sigma_v^2)$ and captures random variation in output due to factors outside the control of the firms. On the other hand, $u \geq 0$ reflects technical inefficiency and η is an unknown scalar parameter. This model considers the non-negative firm effects, u_{it} which increase, decrease or remain constant with time depending on whether $\eta < 0$, $\eta > 0$ or $\eta = 0$, respectively. When $\eta > 0$, firms improve their level of technical efficiency over time. $\tau(i)$ represents the set of T_i time period among the T period for which observations for the *ith* firm are obtained. If we obtain observations at discrete intervals, then $\tau(i)$ would be considered as a subset of the integers, 1, 2,……, T denoting the periods of observations involved. In the present study, we expect technical efficiency to increase for those pharmaceutical firms that engage in R&D and patenting activities. Further, the parameters μ and σ^2, define the statistical properties of the firm effects associated with the terminal period for which we have the observation since in the T th time period for the i^{th} firm, $u_{it} = u_i$, where $i = 1,2,...N$. The model assumption of firm effects as proposed by Stevenson (1980) is a generalization of the half-normal distribution. The exponential specification of the behaviour of the firm effects over time has a rigid parameterization such that technical efficiency must either increase at a decreasing rate $(\eta > 0)$ or decrease at an increasing rate $(\eta < 0)$ or remain constant $(\eta = 0)$.

From equations (1) and (2), it can be shown that the minimum mean-squared-error predictor of the technical efficiency of the i^{th} firm at the t^{th} time period is given as follows:

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

$$= E[\exp(-u_{it})|E_i] = \left\{\frac{1-\phi\left[\eta_{it}\sigma_i^* - \left(\mu_i^*/\sigma_i^*\right)\right]}{1-\phi\left(-\mu_i^*/\sigma_i^*\right)}\right\}\exp\left[-\eta_{it}\mu_i + \frac{1}{2}\eta_{it}^2\sigma_i^{*2}\right] \tag{4}$$

where $E_{it} = v_{it} - u_{it}$ and E_i represents the $(T_i \times 1)$ vector of E_{it}'s associated with the time periods observed for the i th firm.

$$\mu_i^* = \frac{\mu\sigma_v^2 - \eta_i' E_i\sigma^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2} \tag{5}$$

$$\sigma_i^{*2} = \frac{\sigma_v^2\sigma^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2} \tag{6}$$

where, η_i represents the $(T_i \times 1)$ vector of η_{it}'s associated with the time periods observed for the i th firm, and $\phi(.)$represents the distribution function for the standard normal random variable. The predictor of technical efficiency defined in equation (4) can be obtained by substituting the appropriate parameters by their maximum likelihood estimators (Coelli, 1991).

III. Data and Variables

The study is based on data for pharmaceutical firms provided by the Centre for Monitoring Indian Economy (CMIE's) *Prowess* database for the period 1991 to 2003 (years are financial years, starting on April 1 to March 31). Of the total firms, 30 are

foreign-owned companies and the rest 291 are Indian companies. For the econometric study, the dataset includes only those firms that report some R&D spending. This results in an unbalanced panel of 76 firms with 716 total observations. The data on patents granted is obtained from the *Gazette of India, Part III, Section 2*.

The capital variable is the value of net fixed assets deflated by capital stock deflator. The capital stock deflator uses base year 1995 and is a weighted average of the price index of construction and plant and machinery published by the Central Statistical Organization's (CSO) *Monthly Abstract of Statistics* for various years. The weights are derived as the relative shares of construction and plant and machinery given in the *National Income Accounts, January 2004*, published by the CMIE.

The CMIE database does not report the number of employees in a firm. The series on labour was generated by dividing the data on firm-wise wages and salaries with the wage rate (Total emoluments/ Number of employees) for the pharmaceutical industry obtained from various issues of the *Annual Survey of Industries, Summary Results Factory Sector* published by the CS0.

We used the perpetual inventory method to construct the own technology stock of the firm, given as: $RD_{it} = (1-\delta)RD_{i,t-1} + R_{i,t}$, where $RD_{i,t-1}$ is the stock of R&D on research and development by firm i at time t-1 and δ is the rate of depreciation to technical knowledge. And R_{it} is the new investment on research and development. Following earlier studies we take the depreciation rate of 15 percent. The R&D stock deflator (base year 1995) was constructed as a weighted average of the capital stock deflator and the consumer price index for urban non-manual employees obtained from the Government of India's *Economic Survey, 2003-04*. The weights for capital and labour

were determined by wages/net sales and net fixed assets/ net sales, respectively for each firm.

IV. Empirical Results

The stochastic frontier production function for the panel data of Indian pharmaceutical firms is estimated as follows.

$$y_{it} = \beta_0 + \beta_1 k + \beta_2 l + \beta_3 rd + \beta_4 WTOD + \beta_5 PATD + v_{it} - u_{it} \qquad (7)$$

The lower case letter represents the logarithmic transformation of the variables. Gross value added is represented by y_{it}, k represents capital, l for labor and rd represents the stock of research and development. To examine the impact of the setting up of the WTO and a stronger patent regime, we introduce a dummy $WTOD$ that takes the value 1 for 1996 onwards and 0 otherwise. A dummy for patenting firms is also used to see the technical efficiency of firms that successfully engage in R&D and patenting activities, thus $PATD$ takes the value 1 for the year that a patent is granted to a given firm and 0 otherwise. v_{it} and u_{it} are random variables whose distributional properties are explained above in section (2). Maximum-likelihood estimates for these parameters are obtained for five basic models.

Model 1: We have estimated all parameters; Model 2: we assume $\mu = 0$; Model 3: we assume $\eta = 0$; Model 4: $\mu = \eta = 0$; and Model 5: $\gamma = \mu = \eta = 0$.

Model 1 is the stochastic frontier production function (7) in which the firm effects u_{it}, have the time varying structure. In Model 2, the $u_i's$ have half normal-distribution $(\mu_i = 0)$. Model 3 is the time invariant model considered by Battese, Coelli and Colby (1989). Model 4 is the time-invariant model in which the firm effect u_i follows a half

normal distribution. Finally, Model 5 is the traditional average response function in which firms are assumed to be fully technically efficient which in turn implies that the firm effects, u_{it}, are absent from the model.

The results for the above five models are presented in Table 1 for three different cases namely, all firms, non-patenting firms and patenting firms. We have tested the hypothesis for the parameters of the distributions of the u_{it} random variable (firm effects). They are obtained by using the generalized likelihood ratio statistic. The null hypothesis, $H_0 = \gamma = \mu = \eta = 0$, is rejected for both the full sample and the sub-sample of patenting and non-patenting firms. It implies that given the specifications of the stochastic frontier with time varying firm effects, the usual production function is not an adequate representation of our data. We have also tested for the time-invariant models for firm effects. We reject both $H_0 : \mu = \eta = 0$ and $H_0 : \eta = 0$ to support the above hypothesis. This is also valid for both the full sample and the sub-samples. We do not reject the hypothesis of the half normal distribution of u_{it}. Thus, given that the half normal distribution is an adequate representation of the firm effects, we reject the hypothesis that the yearly firm effects are time invariant. Based on the results, it is evident that the hypothesis of time-invariant technical efficiencies of the pharmaceutical firms would be rejected for the full sample. The estimated η from the exponential model in equation (2) is positive for both the full sample and the sub-sample of patenting firms but negative for non-patenting firms. This means technical efficiency is increasing over time for the pharmaceutical industry as a whole and also for the firms engaged in patenting activities. However, efficiency for non-patenting firms shows a declining trend.

Thus, it seems that the positive and increasing efficiency of the full sample is probably due to the predominant effect of patenting firms in the industry.

We estimate the stochastic production frontier given in equation (7) and the estimated results are reported for the full sample (Table 2), the sample of non-patenting firms (Table 3) and sample of patenting firms (Table 4). We notice that the coefficient estimates of all observable variables are of expected signs. The coefficients for the WTO dummy and the patent dummy in the full sample have a positive sign and are statistically significant. It should also be noted that the parameters γ and σ_s^2 of the ML estimation are statistically significant and the log-likelihood value is high enough to surpass the critical value. η is statistically different from zero and indicates a time-varying technical efficiency of the sample firms.

The returns to scale parameter are not significantly different from one for the full sample and the sub-sample of non-patenting firms. Thus, the hypothesis of constant returns to scale would not be rejected using the data. At the same time the returns to scale parameter is significantly different from one for the sub-sample of patenting firms, rejecting the hypothesis of constant returns to scale. In other words, we observe increasing returns to scale for the Indian pharmaceutical firms engaged in R&D and patenting activities.

A. *Technical Efficiency*

As stated above, a firm is said to be technically efficient if the estimated technical efficiency coefficient is 100 percent and technically inefficient otherwise. This means that if an inefficient firm utilizes its factors of production as effectively as an efficient firm does, it should be able to increase its current output to the level that the efficient firm

could achieve using the same factor inputs without increasing its current factor inputs. Using the estimated parameter values for the frontier production function (7), predictions were obtained for the technical efficiencies (4) of individual firms. The average technical inefficiencies for the full sample and sub-sample of patenting and non-patenting firms have been calculated and are presented in Table 5. We have divided the whole period (1991-2003) into three sub-periods to examine the gradual change in technical efficiency starting from the time of liberalization (1991) till the enforcement of the WTO provisions (2003). So, we study technical efficiency over the following four periods, that is, 1991-94; 1995-98; 1999-2003 and 1991-2003.

We observe a gradual improvement in technical efficiency in all types of firms over the period under study. For the sub-period, 1999-2003, when the WTO provisions were enforced to strengthen patent rights for pharmaceuticals, the patenting firms almost reached the frontier, suggesting that stronger patent laws induce greater R&D efforts and improve efficiency. However, the average technical efficiency of all firms for the same period was 0.69, implying that the improvement in technical efficiency for patenting firms was unable to push the industry's output as a whole close to the potential output level. Further, the differences between the technical efficiency of patenting and non-patenting firms should also be noted. While the technical efficiency for non-patenting firms are below the average for all firms, that of patenting firms is above the average for all firms. This is another indication of economies of scale in patenting firms, that is, the patenting firms are able to achieve their potential efficient output by utilizing their production facilities more effectively than their non-patenting counterparts. Thus, we find

that firms engaged in patenting activities are more efficient in a research-intensive industry like pharmaceuticals even in developing countries like India.

V. Conclusion

This paper examines the technical efficiency of the Indian pharmaceutical industry in the light of policy changes in the international and domestic environment since 1995. We find that for the industry as a whole, there is evidence of time-varying technical efficiency for the sample firms. In addition, we find increasing returns to scale for the sub-sample of patenting firms, indicating that firms that successfully undertake R&D activities get high returns in developing countries like India.

The main hypothesis that the setting up of the WTO and the deregulation of the pharmaceutical industry in India has improved the efficiency of the industry is supported by the results of the study. The favourable impact of the WTO and liberalization of the industry on output is evident from the positive and significant sign of the WTO dummy. Moreover, the results on technical efficiency show that patenting firms are close to the frontier and utilize the factors inputs efficiently. Thus, it seems that the new WTO regime of stricter patent rights has provided a stimulus to patenting firms to undertake greater R&D activities in order to effectively compete with pharmaceutical MNCs. It seems that the larger firms with potential for R&D will survive the enforcement of product patents through collaborations with MNCs concerning research joint ventures and contract research. For the pharmaceutical firms engaged in only manufacturing and marketing activities without any focus on research activities, the competition from MNCs could be fierce and may stimulate them to become more research-oriented firms in the long run. In

the final analysis, the stronger patent laws may stimulate even the non-patenting firms to become more research-oriented and efficient in the long run.

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Table 1: Maximum-likelihood estimates of parameters of stochastic production functions for Indian pharmaceutical firms: Full Sample

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
ln (R&D)	0.116***	0.118***	0.120***	0.117***	0.115***
	(.020)	(0.019)	(0.018)	(0.021)	(0.024)
ln (capital)	0.092***	0.094***	0.094***	0.093***	0.091***
	(0.023)	(0.025)	(0.023)	(0.027)	(0.029)
ln (labor)	0.536***	0.538***	0.545***	0.542***	0.535***
	(0.035)	(0.038)	(0.039)	(0.035)	(0.037)
WTO Dummy	0.061**	0.060***	0.061***	0.062**	0.062***
	(0.031)	(0.030)	(0.031)	(0.032)	(0.031)
Patent Dummy	0.013*	0.011	0.012*	0.013*	0.014*
	(0.0075)	(0.0072)	(0.0079)	(0.0076)	(0.0081)
Constant	3.977***	3.976***	3.978***	3.980***	3.976***
	(0.207)	(0.206)	(0.208)	(0.212)	(0.215)
$\sigma_s^2 = \sigma_v^2 + \sigma_u^2$	0.060***	0.057***	0.065***	0.064***	0.066***
	(0.0088)	(0.0084)	(0.0087)	(0.0079)	(0.0089)
$\gamma = \frac{\sigma_u^2}{\sigma_s^2}$	0.623***	0.615***	0.568***	0.589***	0
	(0.058)	(0.054)	(0.059)	(0.062)	
μ	0.460***	0	0.462***	0	0
	(0.110)		(0.129)		
η	0.034	0.031	0	0	0
	(0.023)	(0.027)			
Log likelihood	228.165	228.167	238.166	238.165	238.168

Notes: Standard errors are given in parenthesis
***, **, * denote significance levels at 1, 5 and 10 percent.

Table 2: Maximum-likelihood estimates of parameters of stochastic production functions for Indian pharmaceutical firms: Non-Patenting Firms

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
ln (R&D)	0.104***	0.106***	0.105***	0.107***	0.103***
	(0.027)	(0.029)	(0.024)	(0.024)	(0.027)
ln (capital)	0.216***	0.219***	0.218***	0.216***	0.218***
	(0.044)	(0.046)	(0.044)	(0.045)	(0.044)
ln (labor)	0.405***	0.382***	0.388***	0.400***	0.401***
	(0.039)	(0.033)	(0.038)	(0.037)	(0.035)
WTO Dummy	0.031*	0.032*	0.030*	0.0312*	0.0313*
	(0.0171)	(0.0173)	(0.0170)	(0.0172)	(0.0174)
Constant	3.448***	3.442***	3.445***	3.452***	3.446***
	(0.320)	(0.319)	(0.321)	(0.341)	(0.318)
$\sigma_s^2 = \sigma_v^2 + \sigma_u^2$	0.095***	0.098***	0.097***	0.092***	0.093***
	(0.030)	(0.031)	(0.041)	(0.032)	(0.033)
$\gamma = \frac{\sigma_u^2}{\sigma_s^2}$	0.731***	0.752***	0.777***	0.735***	0
	(0.088)	(0.085)	(0.086)	(0.076)	
μ	0.290***	0	0.295***	0	0
	(0.126)		(0.129)		
η	0.017	0.019	0	0	0
	(0.011)	(0.012)			
Log likelihood	134.801	142.796	141.765	140.834	142.560

Notes: Standard errors are given in parenthesis
***, **, * denote significance levels at 1, 5 and 10 percent.

Table 3: Maximum-likelihood estimates of parameters of stochastic production functions for Indian pharmaceutical firms: Patenting Firms

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
ln (R&D)	0.183***	0.134***	0.136***	0.131***	0.137***
	(0.020)	(0.021)	(0.022)	(0.021)	(0.025)
ln (capital)	0.380***	0.371***	0.371***	0.376***	0.369***
	(0.028)	(0.026)	(0.028)	(0.029)	(0.026)
ln (labor)	0.461***	0.446***	0.459***	0.457***	0.458***
	(0.034)	(0.032)	(0.037)	(0.032)	(0.033)
WTO Dummy	0.051***	0.0525***	0.050***	0.0543***	0.0551***
	(0.0161)	(0.0183)	(0.0150)	(0.0162)	(0.0164)
Constant	1.912***	1.908***	1.917***	1.915***	1.913***
	(0.139)	(0.137)	(0.136)	(0.136)	(0.134)
$\sigma_s^2 = \sigma_v^2 + \sigma_u^2$	0.069***	0.068***	0.069***	0.070***	0.067***
	(0.0089)	(0.0085)	(0.0088)	(0.0087)	(0.0085)
$\gamma = \frac{\sigma_u^2}{\sigma_s^2}$	0.621***	0.620***	0.621***	0.619***	0
	(0.058)	(0.056)	(0.054)	(0.053)	
μ	1.460***	0	1.452***	0	0
	(0.112)		(0.115)		
η	0.068***	0.068***	0	0	0
	(0.023)	(0.021)			
Log likelihood	131.965	132.987	131.884	132.564	132.432

Notes: Standard errors are given in parenthesis
***, **, * denote significance levels at 1, 5 and 10 percent.

Table 4: Test of hypothesis for parameters of the distribution of the firm effects, U_{it}

Assumptions	Null Hypothesis	χ^2 - Statistic	$\chi^2_{0.95}$ value	Decision
Model 1	$\gamma = \mu = \eta = 0$	15.00	8.67	Reject Null
Model 2	$\mu = \eta = 0$	18.02	7.87	Reject Null
Model 3	$\mu = 0$	0.03	6.69	Accept Null
Model 4	$\gamma = \eta = 0$	17.23	7.87	Reject Null
Model 5	$\eta = 0$	22.45	6.69	Reject Null

Table 5: Average technical efficiency among All, Patenting and Non-patenting firms 1991-2003

Types of Firms	Avg.1991-94	Avg. 1995-98	Avg.1999-03	Avg. 1991-03
All Firms	0.62	0.64	0.69	0.68
Patenting Firms	0.89	0.93	0.95	0.92
Non-patenting Firms	0.59	0.63	0.65	0.62

Note: We have taken the four yearly average of the estimated technical efficiency for individual firms.