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Factors responsible for Variation in Technical Efficiency: A Case Study of Indian Manufacturing Industries

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ABSTRACT

The study tries to find out technical efficiency (TE) scores of top five high-produce (according to Gross Value Added) manufacturing industries of India during 2000 - 2022 using Stochastic Frontier Production Function with 3-digit level Annual Survey of Industries data. There is an attempt to highlight the factors responsible for variation in TE over the period by considering some technological, firm-specific structural factors. Main findings are as follows. Larger firms attain higher TE over the period. Structural factors like employers' contribution help to attain efficiency for the industries, employment of more direct workers induces higher TE and higher share of real wages by the workers induces increase in TE of Indian manufacturing industries. Negative impact on TE is observed if the industries employ higher number of contract workers. Policy suggestions may include the incorporation of technological diffusion, easier financial access, adaptation of scale of economies, grabbing of market power, favourable work environment etc. for the Indian manufacturing industries which will help to increase TE over the period thus accelerating the overall development process.

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Introduction

Rapid industrialization is one of the leading ways to achieve economic development in an emerging economy like India. As we know, agro-based economy is a predominant feature of India, the founders of India's independence concentrated on developing the country's industrial sector through which fast expansion of the economy shall take place. Following that trend, one of the main aims of economic reform was to strengthen competition among firms of different industries thus helping them to become more productive and efficient over the period. In fact, the open market competition puts challenges before different domestic firms in regard of their endurance. The economic reform policies adopted by the Government since 1991 became less friendly to the less efficient industries. Hence, for growth and development, a producing unit has to operate efficiently.

To study the economic performance of industrial sector of India, one can bang up on the estimation of efficiency of different manufacturing firms. Technical Efficiency (TE) occurs when the maximum amount of an output is produced for a given set of inputs (output-oriented technical efficiency) or when the minimum amount of inputs are required to produce a given level of output (input-oriented technical efficiency).

The literature review found some studies on measuring TE scores of some Indian industries or a particular industry and the impacts of relevant factors affecting the TEs. Some of them are as follows- Muneer (2024), considering 26 Indian manufacturing industries during 1992-93 to 2019-2020 revealed that the industries faced a decline in average TE by 0.7% implying industrial development due to technological improvement than efficient resource utilisation. Bhat and Kaur (2022), using panel data of Indian IT industry during 2000-2016 with stochastic frontier analysis found that foreign capital, firm age and profit ratio have significant impact on reducing technical inefficiency. Abdulla and Kumar (2021), using unbalanced panel data of 2005-2016, with stochastic frontier analysis, observed varied performance of TE of MSMEs: small scale firms have the highest whereas medium scale firms have the lowest TE scores. Murty and Nagpal (2020), using 'by-production' approach, measured and decomposed TE of Indian Coal-based Thermal Power-Plant. They found that productive efficiency is positively associated with thermodynamic energy efficiency and efficiency levels are generally higher in private and central-sector power-plants compared to state-owned ones. Sue and Nandy (2018) considering Indian Automobile Industry observed that foreign firms generally exhibit higher TE than domestic counterparts.

Theoretically it is known that the existence of various market structures and competitions induced the manufacturing units to focus on their infrastructural improvement, managerial competencies, capacity

building and its utilisation, intensive usage of capital resource and usage of skilled labourers, technological upgradation etc. These attributes have direct or indirect impact on productivity and efficiency of the production units. Hence it would be interesting to throw some light on issues like whether technological capability helps a production unit to raise efficiency level or whether technical efficiency is influenced by large scale operations, absorption of trained labourers etc. Following this theoretical back ground, the objective of this study is to estimate the output-oriented TE of various Indian manufacturing firms and to find out the factors which are responsible for the variation in TE scores.

Model of Measuring Efficiency

Efficiency is one of the important factors in determining the overall performance of a manufacturing unit. To calculate firm-level efficiency, stochastic frontier analysis is used.

The measurement of Technical Efficiency (TE) was effectively started with the analysis of Farre (1957). Output oriented TE is a comparison between observed output and the maximum potential output obtained using given inputs. In this study Stochastic Frontier Production Model (developed by Aigner et al. (1977) is adopted to estimate TE.

Consider a Stochastic Frontier Production Function (SFPF)

$$Y_i = f(X_i, t; \beta)\exp(v_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

representing the maximum producible output by the ith producing unit given the non-negative input vector X_i

β = the corresponding vector of technology parameters and

v_i = a random variable seeking to capture all the random factors that are outside the control of the producer (such as, weather, strikes, factor intensity, implementation of some reform policies, etc.). These random factors are likely to affect the production of maximum possible output.

t = time period.

Actually, the ith producing unit's observed output; Y_i may lie below the frontier output due to say, the presence of workers with lower ability, poor management decisions or inadequate monitoring efforts etc. These shortfalls are captured by Technical Inefficiency of the producing unit. Since the actual output cannot be higher than the frontier output, equation (1) can be modified as

$$Y_i = f(X_i, t; \beta)\exp(v_i)\exp(-u_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

with $u_i \geq 0$ implying that exp(-u_i) ≤ 1.

So, an output-oriented Farrell measure of time-varying TE of the ith producing unit can be presented as

$$\text{TE}_i = \frac{Y_i}{f(X_i, t; \beta)\exp(v_i)} = \exp(-u_i) \ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

for $u_i \geq 0$ and TE_i varies inversely with u_i, $0 \leq TE_i \leq 1$. u_i may be taken as index of inefficiency.

To estimate the time-varying technical inefficiency prevailing across different firms in a particular industry, we follow the methodology of Battese and Coelli (1993) and Lundvall and Battese (2000). From equation (3), it can be noted that v_i and u_i – two error terms are included in the expression. v_i is the usual error term of the model and is independently, identically, normally distributed with mean=*0* and variance=σ^2. u_i measures the magnitude of technical inefficiency in production prevailing in the ith producing unit. It is independently distributed from a normal distribution with mean=μ_i and variance= σ_u^2, truncated at zero. Further it is assumed that there is no correlation between v_i and u_i.

After getting different TE scores of different producing units, one may be naturally interested to stagger on the factors responsible behind the variations in TE scores. To find out the determinants of TEs, some empirical studies have suggested a two-stage procedure. In the first stage, firm-specific TE scores are estimated applying stochastic frontier production functions and in the second stage, the estimated TEs scores are regressed on a number of firm-specific variables like, firm size, capital intensity, trade-related factors etc. It is supposed that these factors might be responsible for the variations in TEs across producing units. In many cases, this two-stage procedure have yielded satisfactory results but it has long been argued that this procedure suffers from an inconsistency problem, originated from the assumption of constant exp(u_i) in the first stage, which may contradict the assumption in the second stage that the predicted efficiencies vary with the firm-specific explanatory variables [Coelli et al. (1998), Kumbhakar and Lovell (2000)].

An alternative approach, developed by Battese and Coelli (1993), can be followed in which the estimation of TE scores and the explanation behind the variations in TE are done simultaneously in a single stage. In our empirical study, we have followed this single-stage procedure.

In this model, u_is are not assumed to follow an identical distribution, rather different u_is should have different means i.e., for each u_i the corresponding mean, before truncation, can be denoted by μ_i, $\forall i = 1(1)n$. So, the assumption regarding the variable u_i is now modified as the following: u_is are independently distributed with same variance σ_u^2, but the mean of each u_i is different to each other: $u_i \sim idN^+(\mu_i, \sigma_u^2)$. The present model is now specified with such a stochastic frontier model in which the inefficiency effects are included as an explicit function of some firm-specific factors/variables and their associated parameters. The SFPF along with the inefficiency effects is estimated through a single-stage Maximum Likelihood Estimation (MLE) method.

The mean Technical Inefficiency is represented by

$$\mu_i = \delta' Z_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

and adding the relation with equation (3) we get the model for our empirical study. In equation (4), μ_i = mean before truncation for the variable u_i.

Z_i = ith producing unit's specific vector that may include exogenous and endogenous variables in explaining the inefficiency effect.

δ = associated parameters to be estimated and δ' is the transpose of δ.

It can be noted here that this assumption is consistent with the assumption that the u_i is a non-negative truncation of $N(\delta' Z_i, \sigma_u^2)$. Furthermore, u_i is specified in such a manner that 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[1]. There may be some literature in which some alternative models are also presented for this purpose but it can be noticed here that those models are obtained as particular cases of the models following the equations (3) and (4). For example, according to Huang and Liu (1991), a non-neutral model can be built if some of the input variables of the model also appear in Z_i. Again, if Z_i vector's first element is unity with non-zero parameter associated with it, while rest of the δ s is zero, we can get the general truncated normal distribution for the u_i (proposed by Stevenson (1980) and Battese et al. (1998). If elements of δ is a null vector, the half-normal distribution for the u_is are obtained. It is to be noted here that Y_i should not be included in the Z_i vector; Z_i may be defined in terms of the level of an input, but not output.

[1] According to Battese and Coelli, [1993, 1998], the expected value of TEi, given ε_i is $E[\exp(-u_i)|\varepsilon_i$

Description of Data and Methodology Used

According to the Annual Survey of Industries (ASI) 2023-24 results released in August 2025, the top five manufacturing industries in India by Gross Value Added (GVA) are: Basic Metals (11.56%), Motor Vehicles/Trailers (9.11%), Chemicals & Chemical Products (8.81%), Food Products (7.40%), and Pharmaceuticals (7.24%). These sectors together account for over 56% of the total industrial output in the organized factory sector in India.

In this study ASI 3-digit level data of these 5 top high-produce manufacturing Industries of India during 2000-2022 is considered. ASI data is relatively more comprehensive and larger in size compared to CMIE data base.

One output-four input production frontier is used in the empirical analysis. Descriptions of the variables like gross value added, gross fixed capital, man-days worked etc are given below-

Gross Value Added (GVA): the ex-factory value of products and by-products manufactured during the accounting year, and the net value of the semi-finished goods, work-in process and also the receipts for industrial and nonindustrial services rendered to others.

Capital (GFCF): the gross fixed capital formation in each year

Fuels (F): nominal value of inputs (both indigenous and imported, including power and fuels)

Materials (M): nominal value of inputs (both indigenous and imported)

Labour (L): total number of man-days worked during the year

Five inefficiency explaining variables are constructed and used in the sub-model to explain the variations in TE of Indian manufacturing industries:

Firm size (I): total value of fuels and materials used is considered as a proxy for the size of a producing unit.

Interestingly, this variable is used as inputs in the SFPF and the same variable is used as one of the factors explaining deviations from the production frontier owing to technical inefficiency. Such procedure of using same variable in the production function and in the inefficiency sub-model is not uncommon in the

efficiency literature[2]. It can be argued that industries with larger firms may have an easier access to superior quality of inputs and may operate with bigger scale, gaining other economic advantages over the industries consisting of smaller firms, hence be able to produce larger value of output incurring the same cost of inputs compared to smaller firms. All in turn, reflected in a higher TE for larger firm size. On the other hand, due to concentration of wealth, efficiently operating management system, industries consisting with smaller firms may be in an advantageous position to produce more efficiently than the larger firms.

Employers' contribution (EC) - The total contribution of the employers in each year.

Contractual workers (CW) - All persons who are not employed directly by an employer but through the third agency, i.e. contractor, are termed as contract workers. Those workers may be employed with or without the knowledge of the principal employer.

Direct workers (DW) – The persons engaged by the factory whether for wages or not, in work connected directly with the manufacturing process and include all administrative, technical and clerical staff as also labour in production of capital assets for factory's own use.

Workers' shares in real wages (WSH) - % of direct wages and salaries to all remuneration capable of being expressed in monetary terms

To estimate the time-varying technical inefficiency prevailing across different firms in a particular industry, the methodology of Battese and Coelli (1993) and Lundvall and Battese (2000) is followed. The stochastic frontier production function is taken to be a translog form due to its flexible nature:

$$ln\, Y_i = \left[\beta_0 + \sum_{j=1}^{5} \beta_j x_{ji} + \sum_{j\leq}^{5} \sum_{k=1}^{5} \beta_{jk} x_{ji} x_{ki}\right] + (v_i - u_i) \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Here the subscript i refers to the ith firm, i=1, 2, 3… n, where n is the number of firms in the industry.

X_{ji} = the amount of jth input used by the ith firm, and

x_{ji} = the natural logarithm of X_{ji}, j=1, 2, 3, 4, 5

There is an inefficiency sub-model in which μ_i, the mean of u_i, is postulated to be determined by

$$\mu_i = \left[\delta_0 + \sum_{m=1}^{r} \delta_j z_{mi} + \sum_{m\leq p=1}^{r} \sum^{r} \delta_{mp} z_{mi} z_{pi}\right] \ldots\ldots\ldots\ldots\ldots\

Here also 'i' refers to the ith firm ranging from 1 to n. n = total number of firms.

Z_{mi} = the firm-specific variable considered to explain the variations in TE scores and

z_{mi} = the natural logarithm of Z_{mi}, the subscript m refers to the number of firm-specific factors included in the Z_i vector and m=1, 2, 3 … r

Finally, one can obtain the expression for elasticity of TE_i. The distributional assumptions of the random error term u_i are made in such a manner, that following Battese and Borca (1997), the elasticity of TE with respect to a given explanatory variable, R_i, is given by

$$\left[\frac{1}{\sigma_u}\left\{\frac{\phi\left(\frac{\mu_i}{\sigma_u}-\sigma_u\right)}{\Phi\left(\frac{\mu_i}{\sigma_u}-\sigma_u\right)}-\frac{\phi\left(\frac{\mu_i}{\sigma_u}\right)}{\Phi\left(\frac{\mu_i}{\sigma_u}\right)}\right\}-1\right]\frac{\partial\mu_i}{\partial\ln R_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ represent probability density function and cumulative distribution function of a standard normal variable, R_i respectively. In our study, R_i denotes one of the following variables: A, I, K/L, W and D. The quantity of $\frac{\partial\mu_i}{\partial\ln R_i}$ is easily found out from the estimated form of equation (6).

Empirical Findings

The maximum-likelihood estimates of the parameters of the SFPF along with inefficiency sub-model defined by equations (5) and (6) are obtained for these industries using the computer program Frontier (Version 4.1) described by Tim Coelli [16]. The results are presented in Table-1.

It is to be noted that equation (6) explains μ_i the mean of the inefficiency variable u_i. So, a higher μ_i indicates a lower expected value of TE. From the results, it is observed that mean TE score is 0.84 implying that these 5 industrial units maintained 84% TE during 2000-2022 (See Table 1).

It is to be noted that a few individual parameter estimates are not statistically significant. Generalized Likelihood Ratio (LR) test is conducted to decide upon the reduction of explanatory variables and also test to whether Cobb-Douglas (CD) production function is a proper representation of the production frontier (See Table 1)

The LR test fails to accept the null hypothesis at 5% level of significance stating that the Translog Production Frontier is a better approximation than CD Production Function. It can also be inferred that frontier's output elasticity with respect to different inputs depend on estimated parameter values and on the levels of the explanatory variables corroborates that Translog is better representation than CD.

It is seen that the null hypothesis of no technical inefficiency among firms is failed to be accepted. Thus, it can be said that none of the firm is cent percent technical efficient (See Appendix A.1).

$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$ measures the proportion of total variation in firm's output due to variation in TE. It is seen that more than 90% variation in firm's output is due to variation in technical inefficiency in production. Positive relation between firm-size (I) and TE implies that larger firms may have an easier access to improved quality of inputs and may operate with bigger scale, gaining other economic advantages (like financial access, market power etc) over the smaller firms, hence be able to produce larger value of output incurring the same cost of inputs compared to smaller firms. All in turn, reflected in a higher TE for larger firm size. Positive, significant association between employers' contribution and TE score implies higher contribution from employers into these industries can acquire efficient management skills, adopt sophisticated advanced technology thus inducing higher TE scores over the years. Negative impact of larger number of engagement of contractual workers on TE suggests that inclusion of contract workers does not help to create dispute-free, conducive work environment, rather their dissociation with the production unit, their gave and take policy, profit motive, insecurity about the job and the interference of the third party (in employing the contractual workers) makes the atmosphere strenuous, cumbersome to some extent thus reducing the TE of the industry across years. It is seen that employing larger number of direct workers helps to increase TE of these industries. Direct workers work with more dedication, try to maintain good work environment. Moreover, adoption of labour-intensive technology (by engaging larger number of direct workers) in a labour surplus economy, like India, will in turn help to generate employment also. Proper and apt regulations regarding work environment in the production unit may help to raise the efficiency of the labourers also, thus helping to improve the TE score of the production unit. Increase in workers' shares in real wages (WSH) has a positive impact on TE as rising wage share implies higher payment to the workers. It will attract skilled workers thus raising the productivity and efficiency of the firms. (See Table 1).

The figures of mean elasticities of technical efficiency with respect to inefficiency-explaining variables shows that the mean elasticity of technical efficiency with respect to firm's size (I) is 0.633 implying that if size of the firm increases by 1%, the average elasticity estimate would imply a decrease in technical efficiency by 63%. Similarly, other factors like employers' contribution (EC), no of direct workers (DW),

workers' shares in real wages (WSH)- all exhibit positive values and no of contractual workers exhibits negative value of elasticity estimates (See Appendix B.1).

Table 1: Estimated Regression Results of Top Five High-produce Industrial Units during 2000-2022

Variable	Parameter	Estimated Parameter Values
Constant	β_0	5.11 (3.25)
Ln GFCF	β_1	3.58 (8.41)
Ln F	β_2	4.23 (6.07)
Ln M	β_3	3.19 (2.58)
Ln L	β_4	-6.14 (-4.07)
$(\text{Ln GFCF})^2$	β_{11}	0.58 (6.67)
$(\text{Ln F})^2$	β_{22}	1.03 (5.83)
$(\text{Ln M})^2$	β_{33}	1.73 (9.53)
$(\text{Ln L})^2$	β_{44}	0.021 (2.24)
Ln GFCF × Ln F	β_{12}	0.32 (1.21)
Ln GFCF × Ln M	β_{13}	1.97 (0.46)
Ln GFCF × Ln L	B_{14}	-0.59 (-0.665)
Ln F × Ln M	β_{23}	2.80 (3.50)
Ln F × Ln L	β_{24}	-4.90 (-3.91)
Ln M × Ln L	β_{34}	-0.075 (-7.46)
Constant	δ_0	4.96 (7.17)
Ln I	δ_1	4.83 (3.32)
Ln EC	δ_2	1.93 (2.62)

Ln CW	δ_3	-2.87 (-4.05)
Ln DW	δ_4	1.30 (7.52)
Ln WSH	δ_5	1.20 (3.04)
$(\text{Ln I})^2$	δ_{11}	2.09 (2.36)
$(\text{Ln EC})^2$	δ_{22}	0.068 (1.92)
$(\text{Ln CW})^2$	δ_{33}	0.087 (2.93)
$(\text{Ln DW})^2$	δ_{44}	0.108 (4.89)
$(\text{Ln WSH})^2$	δ_{55}	0.58 (1.97)
Ln I × Ln EC	δ_{12}	1.61 (0.557)
Ln I × Ln CW	δ_{13}	-1.75 (-7.64)
Ln I × Ln DW	δ_{14}	0.041 (0.138)
Ln I × Ln WSH	δ_{15}	0.051 (3.58)
Ln EC × Ln CW	δ_{23}	-1.81 (-2.31)
Ln EC × Ln DW	δ_{24}	0.477 (2.50)
Ln EC × Ln WSH	δ_{25}	1.35 (0.58)
Ln CW × Ln DW	δ_{34}	-4.68 (-2.41)
Ln CW × Ln WSH	δ_{35}	-0.08 (-1.69)
Ln DW × Ln WSH	δ_{45}	1.57 (2.14)
	$\sigma^2 = \sigma_u^2 + \sigma_v^2$	3.41 (21.33)
	$\gamma = \frac{\sigma_u^2}{\sigma^2}$	10.9 (187.205)

Log-Llikelihood value	1501.147
Mean TE	0.84

Notes: t-statistics are in parentheses

Source: Author's Calculation

Conclusion

The present study examines, using conventional SFPF model, the extent of TE of top five high-produce manufacturing industries of India during 2000 – 2022 using 3-digit level ASI data. The generalized Likelihood Tests with the estimated SFPF suggest that instead of Cobb-Douglas production function, a more flexible form like, Translog production frontier appears to fit the observed data better. The manufacturing industries show mean TE of 0.81 and 90% variations in output may be resulted from variation in TE. Larger firms with better access to financial asset, bigger scale of operation, market power enhance TE of the manufacturing industries. More of employers' contribution helps to incorporate sophisticated advanced technology and skilled management to raise the TE score. Increasing number of direct workers and increase in workers' shares in real wages help to build conducive work environment for higher TE. Increasing number of contractual workers reduces TE so the manufacturing industries can opt for lesser number of contract workers and more of direct workers involved in production process which in turn facilitate the rise in TE of the said industries.

The study reveals that mean elasticity of TE with respect to inefficiency-explaining factors like size, employers' contribution, direct workers, workers' share of real wage imply positive impact and contract workers shows negative impact on values of elasticity estimates. It implies that any change in those factors can has increasing and (or) decreasing effect on TE of manufacturing units of India.

As the study aims to capture the variation in TE of the manufacturing industries with regard to some socio-economic, structural factors of the economy, it would be interesting to highlight the impact of any system shock or external shock on the productivity and efficiency of manufacturing industries in India.

Thus, the future course of plan is to address the query - Has the financial crisis (economic downturn) in 2008 made any perceptible impact on the efficiency levels of Indian manufacturing industries. Under these circumstances one may estimate average TE of the industries and try to examine whether such efficiency has any time trend. Besides, a panel data covering pre and post financial crisis periods can be incorporated to analyse the productivity and efficiency dynamics of Indian manufacturing industries. Additionally, a

disaggregated level study of TE, considering each of the five industries separately along with a comparative analysis would be interesting to work out.

Appendix A

Table A.1: Generalised Likelihood Ratio Tests in the Estimated Stochastic Frontier

Null Hypothesis	Estimated Generalised Likelihood Ratio Statistics	Critical Values		Remarks
		1 %	0.5 %	
$B_{jk} = 0$ for j, k = 1,2,3,4,5 (Cobb-Douglas Function)	90.04	2.132	2.776	Critical Values are from 't' table
$\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_{11} = \delta_{22} = \delta_{33} = \delta_{44} = \delta_{55} = \delta_{12} = \delta_{13} = \delta_{14} = \delta_{15} = \delta_{23} = \delta_{24} = \delta_{25} = \delta_{34} = \delta_{35} = \delta_{45} = 0$ (No Inefficiency Effect)	3654.48	24.384	26.856	The Critical Values for the tests are taken from Table 1 of Kodde and Palm (1986, P 1246)[

All the test-statistics values are significant, even at 0.5% level.

Appendix B

Table B.1: Mean Elasticities of TE with respect to Inefficiency-explaining Variables during 2000-2022

Inefficiency Explaining Factors	Values of Elasticity

I (Firm's Size)	0.63 (0.012)
EC (Employers' Contribution)	0.12 (0.011)
CW (Contractual Workers)	-1.57 (0.005)
DW (Direct Workers)	1.37 (0.002)
WSH (Workers' Share in Real Wage)	2.06 (0.008)

Standard Errors are in the parentheses

Source: Author's Calculation

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