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Examining the Productivity and Technical Efficiency of Industrial Sector using Stochastic Frontier Analysis in India

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Abstract: The purpose of this study is to measure the total factor productivity (TFP) of industrial sector in India at an aggregate level and find the impact of technical inefficiency and other input variables on TFP using stochastic frontier analysis approach. Based on the aggregated data for a period of 29 years, the output productivity is measured as net sales revenue of an industry in a particular year, whereas input is measured as the raw material cost, labor cost, capital employed and research and development (R&D) investment of an industry in a particular year. The TFP is measured based on the functional form of Cobb-Douglas model. The results of the study indicate that material, labor and R&D are the prime drivers of TFP for industrial sector and the industrial sector is suffering from poor productivity due to technical efficiency that is decreasing over time.

1. Introduction

Productivity has always remained a major concern for the economists. It is because with the "same amount of inputs, certain countries, sectors, and firms produce more and others produce less" (Kim and Loayza, 2019). Hence, productivity has always been related to the use and availability of resources (Pekuri *et al*., 2011) and has remained a central theme for firms, sectors, and countries. The recent slowdown in the economies across the globe has led to more intense research on the sources of growth and productivity. Studies of Thye *et al.* (1997), Den and Papell (1998), Easterly (2001) and Jorgenson *et al*. (2008) are indications of that.

Off late, Indian industrial sector has also witnessed a steep decline in its contribution towards GVA. According to the data released by Ministry of Statistics and Programme Implementation (MOSPI, 2021), the contribution of industrial sector is 27.47% towards India's gross value added (GVA). If we examine individually, manufacturing contributes nearly 15.13%, construction 7.55%, mining 2.55%, electricity and water supply 2.65% towards GVA. The growth patterns of productivity in the manufacturing sector of Indian firms were studied by several researchers post liberalization (Das *et al.*, 2017; Deb and Ray, 2013; Ghosh, 2010; Kathuria *et al.*, 2010; Virmani and Hashim, 2011; Sahoo and Narayan, 2018; Sahoo *et al.*, 2022). It was found that the sector was performing better pre-reforms. It was attributed to "technological obsolescence, gradual adoption of new technology and slow effect of learning by doing" (Das *et al.*, 2017; Virmani and Hashim, 2011).

Similarly, Indian industrial sector, despite being one of the major contributors towards economic growth has concerns about poor productivity. A large body of literature exists in the domain of productivity and factors driving productivity. However, those studies have focused on manufacturing and agricultural sector (Satpathy *et al.*, 2017; Das *et al.*, 2017; Deb and Ray, 2013; Ghosh, 2010; Kathuria *et al.*, 2010; Frija *et al.* 2015; Virmani and Hashim, 2011). Very recently, Kumar and Paul (2019) measured the total factor productivity using the Levinsohn–Petrin framework for 62 manufacturing firms using the data for the period of 2008-2015. However, authors in this study discovered a major research gap. Most of the studies in India have been carried out in manufacturing sector and that too at firm level and they use convention panel data regression models. Therefore, keeping in mind the above research gap, authors developed this study with an objective to measure the total factor productivity (TFP) of industrial sector in India at an aggregate level and find the impact of technical efficiency and other inputs on TFP using stochastic frontier analysis (parametric) approach. A few studies in the past have also compared the performance of panel data models using the same panel dataset (Kumbhakar and Heshmati, 1995; Greene, 2005a, 2005b; Emvalomatis, 2009; Wang and Ho, 2010; Kumbhakar *et al.*, 2014; Masoomeh *et al.* 2016). In this way the study contributes to the body of knowledge. The rest of the study is divided into five sections. The next section deals with systematic literature review followed by research methodology, data analysis, discussion on results and conclusion.

2. Review of Literature

2.1. Measure of Productivity

Measuring and comparing the productivity across firms, countries and sectors is not an easy task because there are no standard measures of productivity. O'Mahony and Timmer (2009) in their study quoted that "measuring productivity is a complex statistical process that includes numerous steps which aim at making data comparable over time and across enterprises and countries". Organization for Economic Cooperation and Development (OECD) defined productivity as "a ratio of a volume measure of output to a volume measure of input use" (OECD, 2001). Here, the output and input used for productivity calculation could be expressed in physical (quantities) or financial (value) terms (Frija *et al.*, 2015).

Chau and Walker (1998) defined and measured productivity through total factor productivity (TFP) and it measured the changes of aggregate real output. On the other hand, Ondrej *et al.* (2012), measured productivity by using labor costs, materials, and service value as measure of input and the total revenue of the project as a measure of output. Similarly, Tran and Tookey (2011) measured productivity in terms of capital, investment, labor, and other suitable inputs and outputs. Bankeret al. (1984) estimated the firm's productivity through a process that involves summing the cost of goods sold, selling and general expenses, and capital expenditure and then dividing by output, which was operationalized as sales revenue. Similar approach was adopted by Balsam et al. (2011) and Bryan *et al.* (2013). However, these measures suffer from the problem of subjectivity of the evaluator that can lead to inaccurate and misleading results.

Amongst the measures that have been used by scholars in the past to derive productivity, the most popular one is total factor productivity (TFP). It uses the number of factor inputs in production and, therefore, is more suitable for performance measurement and comparisons across firms and sectors over time (Coelli *et al.*, 2005). There are several ways of measuring TFP, however, the statistical approach of stochastic frontier analysis(SFA) is the most popular (Coelli *et al.*, 2005; Greene, 2008; Johnes, 2004; Kumbhakar*et al.* 2015; Parmeter, 2014).

2.2. Technical Efficiency and Productivity

Variations in the ease of resource reallocation can explain the reasons behind higher productivity of certain countries compared to others. For instance, studies also point to the level of education, regulatory environment, innovation, and technology/research and development (Furman and Hayes, 2004; Griffith *et al.*, 2004; Comin *et al.*, 2008) as drivers of productivity.

Studies of various researchers (Sahuand Narayanan, 2011; Mendi, 2007; Hasan, 2002; Scott-Kemmis and Bell, 1988; Lall, 1987) found that embodied technological intensity helps improve productivity. It is through import of capital goods, which results in better technology infusion.

The Griffith *et al.* (2004) indicates that R&D is statistically and economically important in both technological catch up and innovation. According to them human capital also plays a significant role in productivity growth. Foreign competition drives inefficient domestic producers to exploit scale economies, eliminate waste, adopt best practice technologies, or shut down (James, 2000).

Many of the empirical studies have found the significant role of R&D activities in the determination of productivity (Doraszelski and Jaumandreu, 2013; Griffith *et al.*, 2004; Hall and Mairesse, 1995; Harhoff, 1998; Kafouros, 2005; Leachman *et al.*, 2005; Ray, 2014; Voutsinas and Tsamadias, 2014).

Kalaiand (2020) using the stochastic frontier production approach found the production factors have a significant effect on productivity and the total factor productivity. Overall, the average technical efficiency is decreasing internationally with wide intra-group industrial variability in some countries (Kim and Han, 2001; Quintero *et al.*, 2008; Baten *et al.*, 2009; Philips *et al.*, 2012). There have been few studies that have analysed the productivity trends of Indian manufacturing in the after years of the global crisis (Das *et al.*, 2017; Singh, 2017; Goldar *et al.*, 2017; Goldar, 2015) and suggested that overall, there is a decline in productivity. However, the literature has been majorly silent on the impact of technological efficiency on productivity in India barring few studies. For instance, Sahoo and Narayan (2018) revealed in their study that the TFP growth rates of automobile industry in India are driven by technical efficiency change not by technical progress. Further, in a recent study, Sahoo *et al.* (2022) examined the nexus between export, productivity, and competitiveness in the Indian manufacturing sector and tested the "learning by exporting" and "self-selection" hypotheses using firm-level data relating to Indian manufacturing firms relating to period from 1994 to 2017. The empirical analysis supported the "learning by exporting" hypothesis, but does not support the "self-selection" hypothesis.

They also investigated the impact of export on competitiveness, and the results indicated a positive relationship.

Overall, the literature review can be summed up as: (i) There are several ways to measure the TFP or TFPG, however, no standard procedure exist;(ii) Most of the studies in the past have been carried out at a firm level using the conventional panel regression despite its inherent weaknesses;(iii) Stochastic Frontier Econometric (SFE) modelling is more appropriate approach to model the productivity; however, it has not been used extensively by scholars so far, at least not in India; and (iv) The SFE models help us better understand the impact of technological efficiency on productivity and there is recent international evidence to suggest that average technical efficiency is decreasing across industries. Hence, keeping in mid the above, authors in the study developed an appropriate research methodology.

3. Research Methodology

Every productivity measure relates to a specific producer unit. The current study has taken industry as the producer unit. As in most frontier studies, the Cobb-Douglas model is evaluated as a technology representation (De la Fuente *et al.*, 2009; Cysneiros *et al.*, 2019).

The following is the general forms ofthe Cobb-Douglas modelafter linearization.

The Cobb-Douglas Model

$$\text{Ln } (Y_{i,t}) = \beta_0 + \Sigma\, \beta_m \ln(X_{m,i,t}) + v_{i,t} - u_{i,ts} \qquad \text{(Equation 1)}$$

Here, $Y_{i,t}$ is the output of an industry i during period t; $X_{m,i,t}$ are the various inputs of industry i during period t; $v_{i,t}$ is the random disturbance assumed as normally distributed, with a zero mean and constant variance; and $\grave{\imath}_{i,t}$ is a non-observable and non-negative random error associated with the technical inefficiency. The functional forms of the equation have been discussed in the data analysis section.

The functional forms of the Cobb-Douglas Model (equation 1) and is shown below in equation 2.

$$\text{Ln}(S_{i,t}) = \beta_0 + \beta_1 \ln(M_{i,t}) + \beta_2 \ln(L_{i,t}) + \beta_3 \ln(K_{i,t}) + +\beta_4 \ln(R\&D_{i,t}) + v_{i,t} - u_{i,t} \qquad \text{(Equation 2)}$$

Here, in Cobb-Douglas Model, the error term is divided into two main components. These are the usual random noise component and the inefficiency component. The noise component is measuring measurement errors and other random errors which are beyond the industries' capacity. The other component, $\grave{\imath}_{i,t}$ is assumed to be independently and identically distributed, and it takes a value of 1 when the industry is fully efficient, and a value lower than 0 when the industry faces some technical inefficiencies. Thus, the value of u measures the firm efficiency level which is also expressing how far industries' given output is from its potential output compared other industries of the sample.

The current study uses the data of 10 non-financial industries at an aggregate level. Sales of the industry (Schmidt and Campión, 2004; Tran and Tsionas, 2009) is considered as output of the respective industry. The inputs considered are labor input andcapital input (De la Fuente *et al.,* 2009), material input and investment in R&D (Table 2). For the study, the data of these 10 industries for 29 years (1991-2019) is collected from center for monitoring of Indian economy (CMIE). The study period is long enough to conduct a times series analysis, as well as it consists of 10 panels. The list of industries for which the data is collected is provided in Table 1.

Table 1: List of Industries Included in the Sample

S. No.	*Industry*
1.	Electricity Generation
2.	Aluminum
3.	Cement
4.	Construction Equipment
5.	Construction
6.	Mining
7.	Paint
8.	Pharmaceutical
9.	Plastic Furniture Flooring
10.	Steel

Source: Authors' Own Compilation

Table 2: Variable Definition

Variable	*Definition*
Dependent Variable	
Aggregated Industry Sales (S)	Industrial output is measured as net sales revenue of an industry in a particular year.
Independent Variable	
Material (M)	Industrial input is measured as the raw material cost of an industry in a particular year.
Labor (L)	Industrial input is measured as labor cost of an industry in a particular year.
Capital (K)	Industrial input is measured as Capital employed of an industry in a particular year.
Research and Development (R&D)	Industrial input is measured as the amounts of money spend on R&D by an industry in a particular year.

Source: Authors' Own Compilation

4. Data Analysis

The data analysis here is divided into two sections. In section one, basic descriptive statistics of the data is presented. Table 3 shows the mean, standard deviation (SD), Skewness and kurtosis data of all 10 industries.

Table 3: Descriptive Analysis

Measure (IN Millions)	*Y*	*L*	*K*	*M*	*RD*
			Electricity Generation		
Mean	1499791.00	102404.80	5015019.00	747722.90	832.07
SD	1419073.00	90759.23	5194840.00	759968.70	1083.55
Skewness	0.80	0.61	0.92	0.78	1.39
kurtosis	2.25	1.92	2.34	2.09	3.34
			Aluminum		
Mean	183598.10	13258.97	245632.30	84780.72	281.21
SD	179055.70	12590.31	218134.70	105792.20	401.16
Skewness	2.52	1.78	1.60	2.55	3.72
kurtosis	10.65	6.41	5.36	10.61	17.63
			Cement		
Mean	599577.10	32785.10	695581.90	97295.83	512.41
SD	583759.40	33300.72	752753.90	97899.92	450.54
Skewness	0.77	1.01	1.06	0.79	0.79
kurtosis	2.07	2.59	2.65	2.11	2.58
			Construction Equipment		
Mean	159715.50	16281.10	94193.79	87760.03	766.38
SD	172563.30	16827.84	104408.80	97207.62	812.71
Skewness	1.10	1.13	0.92	1.28	0.88
kurtosis	3.18	2.89	2.11	3.96	2.28
			Construction		
Mean	1759591.00	117899.00	3113918.00	579433.20	1021.17
SD	2057497.00	133335.20	3869940.00	703014.70	1286.62
Skewness	0.80	0.85	0.82	0.83	1.00
kurtosis	2.13	2.27	1.98	2.16	2.58
			Mining		
Mean	1316733.00	239317.00	1731476.00	105104.30	2656.45
SD	1074429.00	199659.50	1514741.00	87515.76	2644.22
Skewness	0.50	0.73	0.71	0.74	1.07
kurtosis	1.83	2.22	1.81	2.38	3.20

Measure (IN Millions)	*Y*	*L*	*K*	*M*	*RD*
			Paint		
Mean	118966.70	6173.48	50861.45	51479.34	624.07
SD	121245.60	6534.82	57146.12	53398.29	666.44
Skewness	0.97	1.24	1.44	1.02	1.14
kurtosis	2.47	3.27	4.01	2.75	3.24
			Pharmaceutical		
Mean	851476.90	308689.10	1077871.00	308689.10	39887.14
SD	874474.30	310849.10	1258162.00	310849.10	46808.00
Skewness	0.98	0.91	1.11	0.91	1.05
kurtosis	2.54	2.40	2.82	2.40	2.76
			Plastic Furniture Flooring		
Mean	99143.38	5155.38	71311.79	58779.62	102.93
SD	103403.70	6320.90	68769.43	62771.71	208.39
Skewness	0.88	1.36	0.71	0.86	2.36
kurtosis	2.26	3.56	1.91	2.18	6.93
			Steel		
Mean	1687301.00	104110.40	1978962.00	913753.10	1966.00
SD	1539311.00	83052.00	1875064.00	908912.00	2007.68
Skewness	0.65	0.50	0.68	0.84	1.10
kurtosis	2.08	1.79	1.77	2.51	2.95
			Aggregate		
Mean	827589.50	94607.43	1407483.00	303479.80	4881.46
SD	1219913.00	163070.20	2686782.00	540790.90	18767.17
Skewness	1.97	2.83	3.01	2.58	5.59
kurtosis	6.33	11.94	12.78	9.38	35.60

Source: Authors' Own Compilation

Results of table 3 suggest that construction is the largest sector among the sample followed by steel, and electricity generation. The data show high Skewness and Kurtosis, which is a sign of non-normal data. Hence, all the study variables have been transformed innatural log function. Further, the data is also tested for heteroscedasticity to make sure that the assumption of normality is not violated.

Table 4: Correlation Matrix

	LnY	*LnL*	*LnCE*	*LnM*	*LnRD*	*Variance inflation factor (VIF)*
LnY	1					
LnL	0.9379*	1				8.18
LnCE	0.2707*	0.3311*	1			1.55
LnM	0.9337*	0.8456*	0.1591*	1		3.73
LnR&D	0.7652*	0.8410*	0.0309	0.7370*	1	4.47

*Significant at 1%
Source: Authors' Own Compilation

Table 4 shows the correlation and VIF of all the study variables. It is important to access Collinearity status of the data. It is a situation where two or more predictor variables in a statistical model are linearly related (Hair *et al*., 2010). It is recommended that an independent variable should be dropped from the study if it exhibits VIF >10 (Hair *et al.,* 2010). The results of Table 4 show that the correlation between material and labor (0.845) and between LnR&D and LnL (0.841) is high. However, the VIF values are <10; and the hence, all the variables were retained for further evaluation.

Table 5: Levin-Lin-Chu Unit-Root Test

Variable	*Adjusted t**	*p-value*
LnY	-12.2978	0.000*
LnL	-11.9751	0.000*
LnM	-12.6986	0.000*
LnK	-3.5691	0.0020*
LnR&D	-11.7735	0.000*

*Significant at 1%
Source: Authors' Own Compilation

Ho: Panels contain unit roots Ha: Panels are stationary

Now, the study variables are tested for Stationarity. Stationarity means that the statistical properties of a process generating a time series do not change over time. Levin-Lin-Chu unit-root test is used to identify the presence of unit root in the panel data. The results are presented in Table 5. The results of Levin-Lin-Chu unit-root test suggest that all the study variables are stationary.

Finally, the base ordinary least square (OLS) model was also tested for heteroskedasticity using Breusch-Pagan / Cook-Weisberg test for heteroscedasticity and the results show that the chi square value is 1.14 (p=0.2860). Hence, the null hypothesis of no heteroscedasticity is accepted and the authors can proceed with stochastic frontier analysis.

Finally, the equation 2 is estimated using Cobb-Douglas model. The results are presented in Table 6.

Table 6: Stochastic Frontier Analysis for Cobb-Douglas Production Function

Variable	*Time-invariant inefficiency model*			*Time-varying decay inefficiency model*		
	β	*Std. Err.*	*P>z*	*β*	*Std. Err.*	*P>z*
LnL	0.213*	0.036	0.000	0.213*	0.036	0.000
LnK	-0.008	0.005	0.131	-0.008	0.010	0.423
LnM	0.680*	0.029	0.000	0.680*	0.029	0.000
LnR&D	0.065*	0.010	0.000	0.065*	0.010	0.000
Intercept	3.202*	0.183	0.000	3.199*	0.221	0.000
Estimate u	0.831*	0.222	0.000	0.831*	0.221	0.000
Ln σ^2_S	-1.401	0.571	0.014	-1.400	0.572	0.014
Estimate γ	3.003*	0.606	0.000	3.004*	0.606	0.000
σ^2_u	0.235	0.141		0.235	0.141	
σ^2_v	0.012	0.001		0.012	0.001	
$\sigma^2_S = \sigma^2_v + \sigma^2_u$	0.246	0.141		0.247	0.141	
Gamma $\gamma = \sigma^2 u/\sigma^2_S$	0.953	0.027		0.953	0.027	
H	NA			-0.00004	0.002	0.979
Wald Test	39341.400*			34316.640*		

*Significant at 1%

Source: Authors' Own Compilation

The Stochastic Frontier analysis for Cobb-Douglas production function is available in two variants, i.e., Time-invariant inefficiency model and Time-varying decay inefficiency model. In Time-invariant inefficiency model the assumption is that inefficiency is time invariant. The results suggest that material, labor, and R&D investment is a positive driver of the industrial productivity in India. Moreover, it can be observed that, 95.3% of the deviation in productivity is due to technical inefficiency ($\gamma = 0.953$), in addition to a technical efficiency that decreases over time ($\eta<0$), with a variance in the distribution of technical efficiency (σ^2_S) estimated in 0.246. To measure and rank the TFP of different sectors, authors used the β coefficient weights and estimated the P score. According to the P score, results in Table 7 and figure 1 show that steel sector have the highest productivity followed by electricity generation and pharmaceutical.

Table 7: Analysis of Productivity Across Sectors

S.No.	*Industry*	*P Score*	*Rank*
1	Electricity Generation	14.51	2
2	Aluminum	12.69	8
3	Cement	12.94	6
4	Construction Equipment	12.72	7
5	Construction	13.73	4
6	Mining	13.67	5
7	Paint	12.18	9
8	Pharmaceutical	14.46	3
9	Plastic Furniture Flooring	11.93	10
10	Steel	14.79	1
	Total	13.36	

Source: Authors' Own Compilation

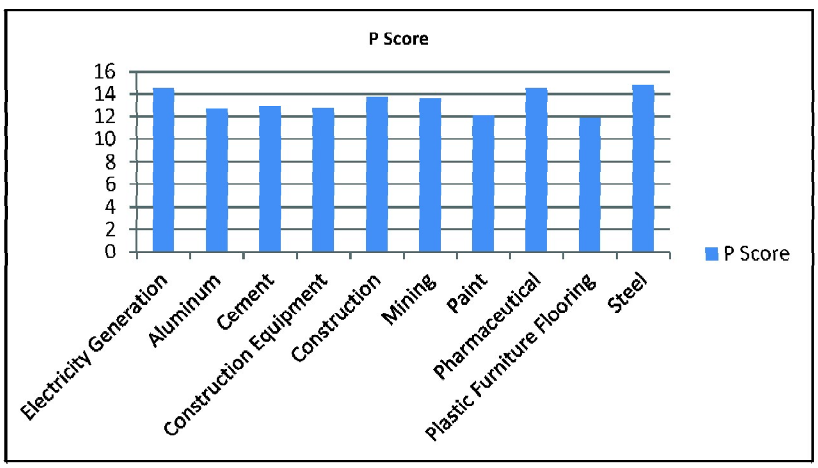

Figure 1: Analysis of Productivity across Sectors

Source: Authors' Own Compilation

To understand how change in technical efficiency has resulted in the change in p score, authors divided the study period into two parts (1991-2005 and 2006-2019). This division was done on the basis that the impact of economic reforms, which were initiated in 1991-92 must be visible post 2005-06. However, the results in Table 8 indicate no major change.

Table 8: Stochastic Frontier Analysis for Cobb-Douglas Production Function

Variable	*Time-invariant inefficiency model (Pre-2005)*			*Time-invariant inefficiency model (Post-2005)*		
	β	*Std. Err.*	*P>z*	β	*Std. Err.*	*P>z*
LnL	0.267*	0.047	0.000	0.253*	0.056	0.000
LnK	0.009	0.014	0.523	-0.022	0.015	0.156
LnM	0.641*	0.037	0.000	0.660*	0.046	0.000
LnRD	0.048*	0.017	0.004	0.063*	0.012	0.000
Intercept	2.878*	0.305	0.000	3.194*	0.309	0.000
Estimate u	0.689*	0.245	0.005	0.776*	0.277	0.005
Ln σ^2_S	-1.564	0.611	0.011	-1.339	0.609	0.028
Estimate γ	3.033*	0.653	0.000	3.058*	0.651	0.000
σ^2_u	0.200	0.128		0.250	0.160	
σ^2_v	0.010	0.001		0.012	0.001	
$\sigma^2_S = \sigma^2_v + \sigma^2_u$	0.209	0.128		0.262	0.160	
Gamma $\gamma = \sigma2u/\sigma2S$	0.954	0.029		0.955	0.028	

*Significant at 1%

Source: Authors' Own Compilation

Based on the coefficient values, the revised P scores are calculated pre-2005 and post 2005. Though, there is no major deviation, it can be observed that the overall productivity has declined post 2005 in most of the sectors except for electricity generation and aluminum and construction equipment (Table 9 and figure 2).

Table 9: Productivity Scores before and after 2005

S. No.	*Industry*	*P Score (Pre-2005)*	*P Score (Post 2005)*
1	Electricity Generation	14.75	14.84
2	Aluminum	12.96	13.02
3	Cement	13.25	13.18
4	Construction Equipment	12.94	13.11
5	Construction	14.05	13.79
6	Mining	13.98	13.96
7	Paint	12.26	13.12
8	Pharmaceutical	14.66	13.34
9	Plastic Furniture Flooring	12.09	13.56
10	Steel	14.96	13.13
	Average	13.59	13.50

Source: Authors' Own Compilation

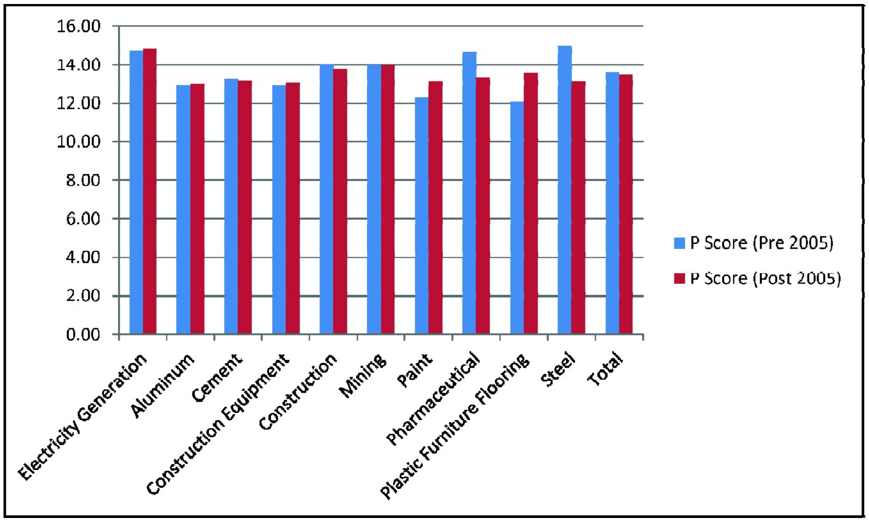

Figure 2: Comparative P Score

Source: Authors' Own Compilation

A comparison of the P scores across years with growth in gross domestic product (GDP) is presented in Table 10 and figure 3. These results highlight that there is a consistent pattern between GGDP and P Score. In fact, GGDP is a leading indicator of the P Score.

Table 10: P Score and Growth in GDP

Year	*P Score*	*GGDP*
1991	14.89	7.41
1992	14.96	8.26
1993	15.02	6.80
1994	13.35	8.85
1995	12.86	3.80
1996	12.86	4.82
1997	13.85	7.86
1998	14.87	6.53
1999	13.24	4.05
2000	13.21	7.92
2001	12.54	7.55
2002	13.51	7.66
2003	14.52	6.39

contd. table 10

Year	*P Score*	*GGDP*
2004	13.59	7.86
2005	12.61	6.18
2006	13.10	7.92
2007	13.52	8.06
2008	14.37	5.46
2009	13.23	3.84
2010	12.27	7.57
2011	13.62	3.09
2012	12.32	4.75
2013	13.81	5.24
2014	14.43	8.50
2015	12.04	5.53
2016	11.48	5.48
2017	11.83	6.66
2018	11.58	1.06
2019	13.96	8.00

Source: Authors' Own Compilation

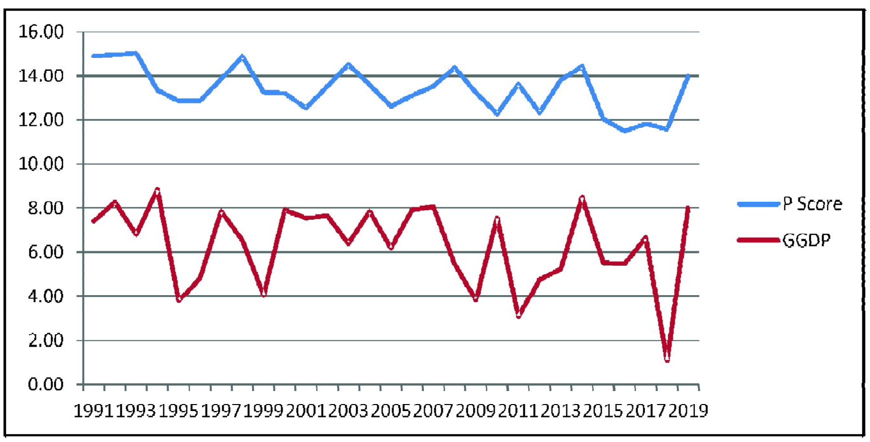

Figure 3: P Score and Growth in GDP

Source: Authors' Own Compilation

5. Discussion and Conclusion

The paper started with the objective to measure the total factor productivity (TFP) of industrial sector in India at an aggregate level finds the impact of technical efficiency and other inputs on TFP using stochastic frontier (parametric) approach. The results of the study indicated that material, labor, and R&D are the prime drivers of productivity in industrial sector in India. Apart from this, the results of stochastic frontier analysis using Cobb-Douglas production function clearly indicated that industrial sector in India is suffering from poor productivity due to technical efficiency that is decreasing over time. To confirm these findings, authors further divided the data into two parts, i.e., pre-2005 and post 2005. The results did not change drastically. In fact, it further strengthens the view that productivity is on a continuous decline. According to the results 95% of this decline can be attributed to technical efficiency, which is huge. The results are in line with Kim and Han (2001), Quintero *et al.* (2008), Baten *et al.* (2009), Philips *et al.* (2012) and Fuente-Mella *et al.* (2020). These scholars in their respective studies have also concluded that productivity in their respective country is on a decline due to technical efficiency which is declining over time. While examining the productivity of manufacturing sector in India, Kumar, and Paul (2019) also came to a similar conclusion, however, they attributed this poor productivity to imperfections in labor and product market.

6. Recommendations

The study contributes to the body of knowledge as to the best of author's knowledge, this the first study in India that measures and examines the productivity of industrial sector using stochastic frontier analysis approach. The industrial sector of India may be benefited from studies as that are presented by us in the literature review as well as benefit from the findings of the current study. Technical inefficiency, which is declining over time, is a major reason for the poor productivity. Thus, like what Fuente-Mella *et al.* (2020) concluded, incorporating information technologies with data analytics platforms can help develop the industrial sector improve its performance. The states and the central government are recommended to have a look at this problem and help industrial sector improve technical inefficiency. They may provide incentives for modernization and upgradation of machines and equipment to help industry. In addition, material, labor, and R&D (innovation) are found to be key drivers of the industrial output. Hence, the sector must focus on improving material and labor productivity as well as use R&D investments to generate additional value and technical efficiency. All this is not going to be easy without government intervention. Hence, the respective governments need to help the sector. A complete digital transformation and data science, and the concept of "Industry 4.0,"can bring the industrial sector of India at par with USA, Germany, and China.

7. Limitations and Scope

Despite best efforts, there are a few limitations of the study. The first and the foremost is the limited sample size. The study is restricted to only 10 industries within industrial sector. Second, the study is using the data at an aggregate industry level rather than the firm level. However, despite these limitations, the study does make important contribution to the body of knowledge.

References

Balsam, S., Fernando, G. & Tripathy, A. (2011). The impact of firm strategy on performance measures used in computing executive compensation. *Journal of Business Research*, 64(2) 2, 187-193.

Banker, R.D., Charnes, A. & Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9) 9, 1078-1092.

Baten, M. A., Kamil, A. A. & Fatama, K. (2009). Technical efficiency in stochastic frontier production model: An application to the manufacturing industry in Bangladesh.*Australian Journal of Basic & Applied Sciences*, 3, 1160–1169.

Bryan, D., Fernando, G. D. & Tripathy, A. (2013). Bankruptcy risk, productivity, and firm strategy.*Review of Accounting and Finance*, 12(4), 309-326.

Chau, K.W. and Walker, A. (1988). The measurement of total factor productivity of the Hong Kong construction industry.*Construction and Production Economics*, 6(3), 209-24.

Coelli, T.J., PrasadaRao, D.S., O'Donnell C.J. & Battese G.E. (2005). *An Introduction to Productivity and Efficiency Analysis*, Second Edition. USA: Springer.

Comin, D., Hobijn, B. & Rovito, E. (2008). Technology Usage Lags.*Journal of Economic Growth*, 13(4), 237–56. https://doi.org/10.1007/s10887-008-9035-5.

Francisco J. A. C., Leiva, V., Liu, S., Marchant, C.& Scalco, P. (2019). A Cobb–Douglas type model with stochastic restrictions: formulation, local influence diagnostics and data analytics in economics. *Quality & Quantity: International Journal of Methodology,* Springer, vol. 53(4), 1693-1719.

Dan, B. & Papell, D.H. (1998). Slowdowns and Meltdowns: Postwar Growth Evidence from 74 Countries.*Review of Economics and Statistics*, 80(4), 561–71.

Das, D.K., Erumban, A.A., Aggarwal, S. & Sengupta, S. (2016). Productivity growth in India under different policy regimes: 1980-2012.in Dale W., Jorgenson, Kyogi, Fukao and Marcel P., Timmer (Eds), The World Economy: Growth or Stagnation? Cambridge University Press.

De la Fuente, H., Berné, C., Pedraja, M. & Rojas, J. L. (2009). Analysis of technical efficiency and marketing productivity for a life insurance company (in Spanish). *Revista Panorama Socioeconómico*, 38, 44–59.

Deb, A.K. & Ray, S.C. (2013). Economic reforms and total factor productivity growth of Indian manufacturing: an inter-state analysis.*Working Paper 2013-04R,* University of Connecticut, Department of Economics.

Doraszelski, U. & Jaumandreu, J. (2013).R&D and productivity: Estimating endogenous productivity. *The Review of Economic Studies*, 80(4), 1338–83.

Easterly, W. (2001). The Middle-Class Consensus and Economic Development.*Journal of Economic Growth*, 6(4), 317–35. https://doi.org/10.1023/A:1012786330095.

Emvalomatis, G. (2009).*Parametric models for dynamic efficiency measurement*, Doctoral dissertation, Department of Agricultural Economics and Rural Sociology, The Pennsylvania State University.

Frija, A., Dhehibi, B., Aw-Hassan, A., Akroush, S. & Ibrahim, A. (2015). Approaches to Total Factor Productivity Measurements in the Agriculture Economy. A report by Food security and better livelihoods for rural dryland communities, available at *https://mel.cgiar.org/reporting/download/hash/TS3DKNYY Approaches to Total Factor Productivity Measurements in the Agriculture Economy* (Accessed on 10th March 2021).

Fuente-Mella, H.D.L., Fuentes, J.L.R. & Leiva, V. (2020). Econometric modeling of productivity and technical efficiency in the Chilean manufacturing industry.*Computers & Industrial Engineering*, 139, 105793, *https://doi.org/10.1016/j.cie.2019.04.006*.

Furman, J. L. & Hayes, R. (2004). Catching up or Standing Still? National Innovative Productivity among 'follower' Countries, 1978-1999.*Research Policy*, 33(9), 1329–54. *https://doi.org/10.1016/j.respol.2004.09.006*.

Ghosh, S. (2010). Economic reforms and manufacturing productivity: evidence from India.*EERI Research Paper Series, No. 32/2010*, Economics and Econometrics Research Institute (EERI), Brussels.

Goldar, B. & Aggarwal, S.C. (2010).Informalization of industrial labour in India: are labour market rigidities and growing import competition to blame? Working Papers id:3125, eSocial Sciences, available at: www.isid.ac.in/pu/conference/dec_10_conf/Papers/BishwanathGoldar.pdf

Goldar, B., Krishna, K.L., Aggarwal, S.C., Das, D.K., Erumban, A.A. & Das, P.C. (2017). Productivity growth in India since the 1980s: the KLEMS approach.*Indian Economic Review*, 52(1-2), 37, available at: *https://doi.org/10.1007/s41775-017-0002-y.*

Greene, W. (2005a). Fixed and random effects in stochastic frontier models.*Journal of Productivity Analysis*, 23, 7–32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model.*Journal of Econometrics*, 126, 269–303.

Greene, W. H. (2008). *The econometric approach to efficiency analysis*, In H. O. Fried, C. A. K. Lovell, & S. S. Schmidt (Eds.), The measurement of productive efficiency and productivity growth (92–250). Oxford: Oxford University Press.

Griffith, R., Redding, S. & Reenen, J.V. (2004). Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries.*The Review of Economics and Statistics*, 86(4), 883–95. https://doi.org/10.1162/0034653043125194.

Hall, B.H. & Mairesse, J. (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics*, 65(1), 263–93.

Harhoff, D. (1998). Are there financing constraints for R&D and investment in German manufacturing firms?*Annals of Economics and Statistics*, 49–50, 421–56.

Hasan, R. (2002). The impact of imported and domestic technologies on the productivity of firms: Panel data evidence from Indian manufacturing firms.*Journal of Development Economics*, 69(1), 23–49.

James, T. R. (2000). Manufacturing Firms in Developing Countries: How Well Do They Do, and Why?*Journal of Economic Literature*, 38, 11–44.

Johnes, J. (2004).*Efficiency measurement*, In G. Johnes, & J. Johnes (Eds.), International handbook on the economics of education (613–742). Cheltenham, UK: Edward Elgar Publications.

Jorgenson, D. W., Ho, M.S. & Stiroh, K.J. (2008). A Retrospective Look at the US Productivity Growth Resurgence. *Journal of Economic Perspectives*, 22(1), 3–24. https://doi.org/10.1257/jep.22.1.3.

Kafouros, M.I. (2005). R&D and productivity growth: Evidence from the UK.*Economics of Innovation and New Technology*, 14(6), 479–97.

Kalai, M. & Kamel, H. (2020). Total Factor Productivity Growth, Technological Progress and Technical Efficiency Changes: Productivity Change Dimensions in Tunisia.*Journal of Quantitative Methods*, 4(2), 76-100. *https://doi.org/10.29145/2020/jqm/040204*

Kathuria, V., Raj, S.N., Rajesh. & Sen, K. (2010). Organised versus unorganised manufacturing performance in the post-reform period. *Economic and Political Weekly*, pp. 55-64.

Kim, S. & Han, G. (2001). A decomposition of total factor productivity growth in Korean manufacturing industries: A stochastic frontier approach.*Journal of Productivity Analysis,* 16, 269–281.

Kim, Y.E. & Loayza, N.V. (2019). Productivity Growth: Patterns and Determinants across the World.*Policy Research Working Paper No. 8852*, Development Economics Development Research Group.

Kumar, R.A. & Paul, M. (2019). Industry level analysis of productivity growth under market imperfections.*Indian Growth and Development Review*, 13(1), 155-174.

Kumbhakar, S. C., Wang, H.J. & Horncastle, A. P. (2015). *A practioner's guide to stochastic frontier analysis using STATA*, New York: Cambridge University Press.

Kumbhakar, S.C. & Hjalmarsson, L. (1995). Labour-use efficiency in Swedish social insurance offices.*Journal of Applied Econometrics*, 10, 33–47.

Kumbhakar, S.C., Lien, G. & Hardaker, J.B. (2014). Technical efficiency in competing panel data models: a study of Norwegian grain farming.*Journal of Productivity Analysis*,41(2), 321-337.

Lall, S. (1987).*Learning to industrialize*, New York: The Macmillan Press.

Leachman, C., Pegels, C.C. & Shin, S.K. (2005). Manufacturing performance: Evaluation and determinants.*International Journal of Operations and Production Management*, 25(9), pp. 851–74.

Masoomeh, R. Almas, H., Ghader, D. & Esmail, P. (2016). A Comparison of Panel Data Models in Estimating Technical Efficiency.*IZA Discussion Papers 9807*, Institute of Labor Economics (IZA).

Mendi, P. (2007). Trade in disembodied technology and total factor productivity in OECD countries.*Research Policy*, 36(1), 121–33.

Ministry of Statistics and Programme Implementation (MOSPI, 2021), *http://statisticstimes.com/economy/country/india-gdp-sectorwise.php* (Accessed on 15th March 2021).

O'Mahony, M. & Timmer, M.P. (2009). Output, input and productivity measures at the industry level: The EU KLEMS database.*The Economic Journal,* 119, 374-403.

OECD (2001). Measuring Productivity – Measurement of Aggregate and Industry-Level Productivity Growth-OECD Manual, *Organisation for Economic Cooperation and Development*, Paris.

Ondrej, M., Jiri, H. & Jan, H. (2012). Estimating Productivity of Software Development Using the Total Factor Productivity Approach.*International Journal of Engineering Business Management*, 4, 1-7.

Parmeter, C. F. (2014). Efficiency analysis: A primer on recent advances.*Foundations and Trends in Econometrics*, 77(3–4), 191–385.

Pekuri, A., Haapasalo, H. & Herrala, M. (2011). Productivity and Performance Management – Managerial Practices in the Construction Industry.*International Journal of Performance Measurement*, 1, 39-58.

Philips, N. O. O., Igberi Christiana, O., & Mbanasor, J. A. (2012). Determinants of productivity among manufacturing firms in South-Eastern Nigeria: Cobb-Douglas stochastic frontier production function approach.*China-USA Business Review*, 11, 1385–1393.

Quintero, J. D., Prieto, W. O., Barrios, F., Guardo, L., & Elena, L. (2008). Determinants of technical efficiency in Colombian companies, 2001–2004 (in Spanish).*SemestreEconomico,* 11, 11–34.

Ray, S. (2014). What explains the productivity decline in manufacturing in the nineties in India?*Indian Council for Research on International Economic Relations Working Paper No. 289.Indian Council for Research on International Economic Relations*, New Delhi, India.

Sahoo,P.K. &Rath, B.N. (2018). Productivity growth, efficiency change and source of inefficiency: evidence from the Indian automobile industry. *InternationalJournal of Automotive Technology and Management*, 18(1), 59–74. doi:10.1504/IJATM.2018.090174.

Sahoo, P.K.Rath, B.N.&Viet Le, (2022). Nexus between export, productivity, and competitiveness in the Indian manufacturing sector.*Journal of Asian Economics*, Volume 79, 2022, 101454, ISSN 1049-0078, *https://doi.org/10.1016/j.asieco.2022.101454*.

Sahu, S., & Narayanan, K. (2011).Total factor productivity and energy intensity in Indian manufacturing: A cross-sectional study.*International Journal of Energy Economics and Policy*, 1(2), 47–58.

Satpathy, L. D., Chatterjee, B. & Mahakud, J. (2017). Firm Characteristics and Total Factor Productivity: Evidence from Indian Manufacturing Firms. *Margin:The Journal of Applied Economic Research*, 111(1), 77–98. doi:10.1177/0973801016676013

Schmidt, G. & Campión, P. (2004). Analysis of efficiency in the Italian manufacturing sector: The stochastic frontier approach (in Spanish), *Bahía Blanca, Argentina: II National Congress of Postgraduate Students in Economics*.

Singh, H. & Vardhana, (2017). Trade policy reform in India since 1991. Brookings India Working Paper 02, March 2017.2

Tran, K. C. & Tsionas, E. G. (2009). Estimation of nonparametric inefficiency effects stochastic frontier models with an application to British manufacturing.*Economic Modelling*, 26, 904–909.

Tran, V. & Tookey, J. (2011). Labour productivity in the New Zealand construction industry: a thorough investigation.*Australasian Journal of Construction Economics and Building*, 41(1), 41-60.

Virmani, A. & Hashim, D.A. (2011). J-Curve of productivity and growth: Indian manufacturing postliberalisation.*IMF (International Monetary Fund) Working Paper No.WP/11/163*, International Monetary Fund.

Voutsinas, I. & Tsamadias, C. (2014). Does research and development capital affect total factor productivity? Evidence from Greece.*Economics of Innovation and New Technology*, 23(7), 631–51.

Wang, H.J. & Ho, C.W. (2010). Estimating fixed-effect panel data stochastic frontier models by model transformation.*Journal of Econometrics*, 157, 286–296.